Essays on Electricity Markets

Information and Trading

Ewa Lazarczyk Carlson

STOCKHOLM SCHOOL OF ECONOMICS

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Dissertation for the Degree of Doctor of Philosophy, Ph.D., in Economics
Stockholm School of Economics, 2014

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ISBN 978-91-7258-927-8 (printed)
ISBN 978-91-7258-928-5 (pdf)

Front cover illustration:

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Back cover photo:
Fredrik Eriksson, 2011

Printed by:

Ineko, Göteborg, 2014

Keywords:

Congestion management, wholesale electricity market, transmission network, nodal pricing, zonal pricing, counter-trading, discriminatory pricing, Urgent Market Messages (UMMs), news, private information, unplanned failures, withholding, economic incentives, intra-day electricity market, forward premia

To
My Polish and Swedish Family
Dla mojej polsko-szwedzkiej rodziny

Foreword

This volume is the result of a research project carried out at the Department of Economics at the Stockholm School of Economics (SSE).

This volume is submitted as a doctor's thesis at SSE. In keeping with the policies of SSE, the author has been entirely free to conduct and present her research in the manner of her choosing as an expression of her own ideas.

Göran Lindqvist

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Acknowledgements

Many people have contributed to this thesis; this is time and place to thank them.

First, I would like to thank my supervisor Richard Friberg and colleagues from The Economics of Electricity Markets program at the Research Institute of Industrial Economics, IFN: Pär Holmberg, Thomas Tangerås, Sven-Olof Fridolfsson, Sara Fogelberg and Erik Lundin.

Richard's support and encouragement were very important to me. His door has always been open to me and he took time to listen, discuss various aspects of my work and taught me the skill of "writing papers". Pär – my co-author – had lots of patience while explaining the mechanisms of electricity markets and was always a great fun to talk, not only about the power grid but for e.g. Belgian crime novels too! Thomas and Sven took time to discuss different research ideas. Thanks to Thomas, Pär and Sven-Olof I was introduced into the meanders of the functioning of electricity markets. Another important person, with whom I spent many working hours this last year is my co-author Sara Fogelberg. Sara: thank you for all the discussion and fun we had; for being not only a colleague but as well a friend. I want as well to thank Erik Lundin for all the discussions and being an excellent office mate.

Some other people that I feel lucky to have met are: Chloe le Coq, Johannes Mauritzen, Mark Voorneveld and my fellow PhD students. Chloe: thank you for the meetings and conversations that we had; Johannes: thanks to you I have learned R! Mark: our gym sessions, teatimes and lunches were very important to me.

I consider myself fortunate for being a part of two excellent research institutions in Stockholm: Stockholm School of Economics and IFN. I was fortunate to meet brilliant researchers both at the School and at the Institute. I would like to thank all of them for providing a great research environment and inspiration for work. I need also to mention that all this would not be possible without help form the administrative staff at both places; I would especially like to thank Ritva Kiviharju, Elisabeth Gustafsson, Marta Benkestock and Jörgen Nilson.

During my studies I had a chance to spend six weeks at Stanford – I am grateful to Frank Wolak and Kathy Lung for enabling my stay.

I would like to thank my Polish and Swedish family for the continuous support. An important person who helped me throughout my PhD studies, with whom I discussed all my research ideas – the ones that are in this book, but as well those that have not yet been turned into papers, person who had enormous patience to introduce me to Python, helped me with solving all my programming problems and did not complain about my "working weekends" - Nils Carlson. Nils: thank you for being there for me!

Last but not least, I am grateful for the financial support provided by the IFN research program The Economics of Electricity Markets and by the Jan Wallander and Tom Hedelius Foundation, which have made it possible to fulfil this project.

Po pięciu latach spędzonych na studiach doktoranckich w Sztokholmie mogę śmiało powiedzieć, że nie byłoby mnie tu gdyby nie wsparcie rodziny i przyjaciół. Dziękuję przede wszystkim: Rodzicom za doping w dążeniu do celu, Ninie za tony maili, którymi rozweselała mój dzień i zwracała uwagę, że poza ekonomią istnieją również inne istotne zagadnienia, babci Wandzi, babci Grażynce i dziadkowi Januszowi za to, że nigdy nie zwątpili w moje naukowe zaangażownie, cioci Eli i wujkowi Rafałowi za wsparcie telefoniczno-medyczne i wielkie rodzinne wakacje, oraz dziewczynom z mojej warszawskiej listy mailingowej: Izie, Aśce i Ance – dzięki Wam ładowałam i nadal doładowuję moje akumulatory!

Stockholm, July 28, 2014

Ewa Lazarczyk Carlson

Contents

Introduction

This dissertation consists of four essays all discussing the topic of electricity markets. It does not provide a full picture but is rather a selection of topics revolving around the issues that I have been working on during these last few years and found particularly interesting. Two of the essays are pieces of joint work: one with Pär Holmberg and the other with Sara Fogelberg. Two main topics emerge in this work: congestion management and the impact of information on the price formation process.

The concept of congestion management is linked with the necessity of an instantaneous balancing of demand and supply in the electricity markets. Transmission constraints, that are a result of the physical properties of the electrical grid, can be managed in various ways. In Europe the EU's regulations recommend market-based designs that offer secure and efficient handling of transmission congestion. The three most common designs are nodal, zonal and discriminatory pricing. In the nodal design the electrical network is divided into nodes and electricity prices are calculated for each and every one of them; this is a design that reflects transmission cost which is equal to the price difference between the exporting and importing node. The zonal pricing model groups several nodes into one zone. These zones differ in size; they can cover a whole country or just a region. Each of the zones has a uniform price and it considers only the congestion between zones; the internal congestion often has to be solved with an additional mechanism – a redispatch. The third design – discriminatory pricing – considers all transmission constraints but there is no uniform market price as the accepted offers are paid as bid. Nodal pricing is widely used in the USA; it is also present in Argentina, Chile, New Zealand, Russia and Singapore. The zonal design is common across European markets while Italy, Iran and British real-time market use the discriminatory design.

Congestion management is discussed in the first essay: **Comparison of congestion management techniques: Nodal, zonal and discriminatory pricing**, where a game-theoretical model evaluating the three most commonly used market designs for managing congestion is presented. The paper shows that discriminatory, nodal and zonal pricing designs, result in the same efficient dispatch of electricity. It, however, points to long-term inefficiencies emerging from additional payments to producers located in export-constrained nodes, that are present in the zonal pricing system when internal, intra-zonal congestion is solved with counter-trading.

The three other articles empirically investigate the role of information in the price formation process. Two of them investigate the impact of news on electricity prices. The third one uses the information about sudden failures of electricity production to discuss certain issues of market power.

The impact of information on prices has been studied thoroughly in the literature. Among topics discussed by different authors are: the impact of public news (Goodhart et al. 1993; Ederington and Lee 1993) and private information on the behaviour of traders and through them on prices (microstructure approach: O'Hara 1995, Brunnermeier 2001, Baker and Kiymaz 2013); the speed of price adjustment to news - instantaneous or lagged (DeGennaro and Shrieves 1997); and the impact of news on the volatility of prices (Goodhart et al. 1993). A concept linked with the impact of information on prices is *market efficiency* (Fama 1970). An efficient market is one where trading on available information fails to provide abnormal profit (Dimson and Mussavian 2000). There are three forms of informational market efficiency depending on the type of information available: a weak form, a semi-strong and a strong form. The weak form claims, that "prices fully reflect the information implicit in the sequence of past prices". The semi-strong claims that prices reflect all relevant publicly available information and the strong form asserts that information that is known to any participant is reflected in prices. The studies of the semi-strong form of market efficiency hypothesis are based mostly on event studies verifying the speed of price adjustment to the new information. A market is strong form efficient if prices contain both public and private information. This form of market efficiency rules out for example, insider trading as prices already reflect this private information.

In my papers I do not directly relate to the efficient market hypothesis, nor do I test for its presence. I do, however, study how information affects prices. The empirical analysis in these articles is based on the Urgent Market Messages (UMMs) dataset that holds information about all sudden and scheduled outages that happened in the Nordic electricity market, Nord Pool, since 2006.

Market participants operating in Nord Pool are obliged to inform about changes to power generation, transmission and consumption that are larger than 100 MW and last for longer than 60 minutes. They inform about the events which alter conditions on the power grid through a channel called Urgent Market Messages. UMMs can be roughly divided into two categories: failures and scheduled maintenance. Information about failures has to be disclosed within 60 minutes of the discovery of the problem. There is no such rule in case of maintenance announcements; some maintenance plans are made public even three years ahead, as in the case of Swedish nuclear power plants, some are reported much closer to the event. From a UMM market participants can learn the identity of the issuer, name of the company, category – producer, consumer or Transmission System Operator (TSO) – size of the outage, and often there is information about the forecasted end of the outage. Messages issued by a TSO inform about changes to transmission capacity with details about the capacity of the line in question and the time frame of the capacity limitation. Moreover, market participants can differentiate between a message that informs about an event on the electrical grid for the first time – new message – and a message that brings additional information about an event that has already been announced – a follow-up.

Similar information systems are now being introduced in Europe where over the last couple of years the European Commission has been introducing regulation on the integrity and transparency of wholesale electricity markets. The regulation requires that "the planned unavailability of 100 MW or more of a generation unit including changes of 100 MW or more in the planned unavailability of that generation unit" are to be publicly disclosed as soon as possible. In Nord Pool such a compulsory "news" system exists since 2004 and between 2004 and 2012 it has registered over fifty thousands messages informing about changed conditions on the Nord Pool power grid. Therefore, it provides good grounds for exploring the impact of news about market fundamentals on prices.

In **Market-specific news and its impact on forward premia on electricity markets** I study, how publicly announced news about changed characteristics on the electrical grid affect price difference between the electricity to be delivered at the same time but traded several hours apart. The short term forward premium is defined here as the difference between the day-ahead and the intra-day electricity price for the product to be delivered at the same time.

I show that short time premia exist on Nord Pool. Their signs fluctuate over time, being mostly negative which indicates that in peak hours the intra-day price is higher than the day-ahead price. I construct a variable counting failure-hours that became publicly known in between the biddings on the two markets and relate it to the formation of price differences between those markets. A more detailed analysis of the messages reveals that fuel used by generators reporting news is also of importance. Additionally I verify the effect of the size of an outage on prices. To the best of my knowledge this is the first study of premia that explicitly takes into account problems on the grid and therefore provides a better understanding of changes in market fundamentals and of the consequences they have on prices.

Strategic withholding through production failures constitutes the third chapter of this dissertation. It proposes a method verifying whether production failures are caused only by technical problems or whether economic incentives play a role when electricity producers announce sudden outages. As the economic incentives might differ depending on whether a generator decides on a new failure or on the prolongation of an existing outage, we test separately for the effect on prices of new messages and follow-ups. The findings confirm the hypothesis that the economic incentives are more important when deciding on the scope of a failure - that is, the size and duration of the failure measured through follow-up messages - as compared to the decision of whether to report a new failure. Moreover, the size of the effect depends on the type of fuel used for electricity generation.

The last essay: **Private and public information on the Nordic intra-day electricity market** relates to the strong form market efficiency and looks for the evidence of a systematic use of private information in electricity trading. I explore the UMMs dataset and relate messages to trades that took place on the Nord Pool intra-day market in years 2010 – 2012. I divide the time of news arrival into three phases: the preannouncement period – the interval up to fifteen minutes before the public announcement of a message, the contemporaneous period – the interval up to fifteen minutes after the announcement of a message, and the post-announcement period – the interval between fifteen to sixty minutes after the announcement of a message. I find that messages affect the mean price levels but do not affect the volatility of prices. No effect of news on the prices and volumes is seen in the preannouncement period, indicating that even if private information exists it is not being systematically used for trading on the intra-day market.

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Chapter 1

Comparison of congestion management techniques: Nodal, zonal and discriminatory pricing*

Abstract: Wholesale electricity markets use different market designs to handle congestion in the transmission network. We compare nodal, zonal and discriminatory pricing in general networks with transmission constraints and loop flows. We conclude that in large games with many producers and certain information, the three market designs result in the same efficient dispatch. However, zonal pricing with counter-trading results in additional payments to producers in export-constrained nodes, which leads to inefficient investments in the long-run.

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* This paper is a joint work with Pär Holmberg (IFN), and a version of this paper is forthcoming in *Energy Economics* (2015). We are grateful for very helpful comments from Richard Friberg, Sven-Olof Fridolfsson, Jenny Fridström, Håkan Pihl, Thomas Tangerås, Bert Willems, anonymous referees, seminar participants at Stockholm School of Economics, (IFN) and the Swedish Ministry of Enterprise, Energy and Communications, and conference participants at IAEE 2011 in Stockholm, EWGCFM 2012 in London and EPRG Online Symposium on Electricity Transmission Pricing and Congestion Management. We also want to thank Erik Lundin for research assistance, and Christina Lönnblad and Dina Neiman for proof-reading our paper. The work has been financially supported by the research program The Economics of Electricity Markets and the Torsten Söderberg foundation.

1.1. Introduction

Storage possibilities are negligible in most electric power networks, so demand and supply must be instantly balanced. One consequence is that transmission constraints and the way they are managed can have a large influence on market prices. The European Union's regulation 1228/2003 (amended in 2006) sets out guidelines for how congestion should be managed in Europe. System operators should coordinate their decisions and choose designs that are secure, efficient, transparent and market based.

In this paper, we compare the efficiency and welfare distribution of three market designs that are in operation in real-time electricity markets: nodal, zonal and discriminatory pricing. Characteristics of the three designs are summarized in Table 1. The zonal market is special in that it has two stages: a zonal clearing and a redispatch. We show that in competitive markets without uncertainties the three designs result in the same efficient dispatch. However, zonal pricing with a market based redispatch (counter-trading) results in additional payments to producers in export-constrained nodes, as they can make an arbitrage profit from price differences between the zonal market and the redispatch stage. This strategy is often referred to as the *increase-decrease* (inc-dec) game. This is the first paper that proves these results for general networks with general production costs. Dijk and Willems (2011) are closest to our study. However, their analysis is limited to two-node networks and linear production costs. The parallel study by Ruderer and Zöttl (2012) is also analyzing similar issues, but the redispatch of the zonal market that they consider is not market based, thus their model does not capture the increase-decrease game.

Table 1: Summary of the three congestion management techniques.

Congestion management technique	Considered transmission constraints	Auction format	Auction format
		Uniform-price	Pay-as-bid
Nodal	All	X	
Discriminatory	All		X
Zonal –stage 1	Inter-zonal	X	
Redispatch –stage 2	Intra-zonal		X

1.1.1. Congestion management techniques

Producers submit offers to real-time markets just before electricity is going to be produced and delivered to consumers. During the delivery period, the system operator accepts offers in order to clear the real-time market, taking transmission constraints into account. The auction design decides upon accepted offers and their payments. Nodal pricing or locational marginal pricing (LMP) acknowledges that location is an important aspect of electricity which should be reflected in its price, so all accepted offers are paid a local uniform-price associated with each node of the electricity network (Schweppe et al., 1988; Hogan, 1992; Chao and Peck, 1996; Hsu, 1997). This design is used in Argentina, Chile, New Zealand, Russia, Singapore and in several U.S. states, e.g. Southwest Power Pool (SPP), California, New England, New York, PJM[1] and Texas. Nodal pricing is not yet used inside the European Union. However, Poland has serious discussions about implementing this design.

Under discriminatory pricing, where accepted offers are paid as bid, there is no uniform market price. Still, the system operator considers all transmission constraints when accepting offers, so there is locational pricing in the sense that production in import-constrained nodes can bid higher than production in export constrained nodes and still be accepted. Discrim-

[1] PJM is the largest deregulated wholesale electricity market, covering all or parts of 13 U.S. states and the District of Columbia.

inatory pricing is used in Iran, in the British real-time market, and Italy has decided to implement it as well. A consequence of the pay-as-bid format is that accepted production is paid its stated production cost. Thus one (somewhat naïve) motivation for this auction format is that if producers would bid their true cost, then this format would increase consumers' and/or the auctioneer's welfare at producers' expense.

The third type of congestion management is zonal pricing. Markets, which use this design, consider inter-zonal congestion, but have a uniform market price inside each region, typically a country (continental Europe) or a state (Australia), regardless of transmission congestion inside the region. Denmark, Norway and Sweden[2] are also divided into several zones, but this division is motivated by properties of the network rather than by borders of administrative regions.[3] Britain is one zone in its day-ahead market, but uses discriminatory pricing in the real-time market. Initially the zonal design was thought to minimize the complexity of the pricing settlement and politically it is sometimes more acceptable to have just one price in a country/state.[4] Originally, zonal pricing was also used in the deregulated electricity markets of the U.S., but they have now switched to nodal pricing, at least for generation. One reason for this change in the U.S. is that zonal pricing is, contrary to its purpose, actually quite complex and the pricing system is not very transparent under the hood. The main problem with the zonal design is that after the zones of the real-time market have been cleared the system operator needs to order redispatches if transmission lines inside a zone would otherwise be overloaded. Such a redispatch increases accepted supply in import-constrained nodes and reduces it in export constrained nodes in order to relax intra-zonal congestion. There are alternative ways of compensating producers for their costs associated with these adjustments. The

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[2] The Swedish government introduced four zones in Sweden from November 2011, as a result of an antitrust settlement between the European commission and the Swedish network operator (Sadowska and Willems, 2012).

[3] The optimal definition of zones for a given network is studied by e.g. Stoft (1997), Bjørndal and Jörnsten (2001) and Ehrenmann and Smeers (2005).

[4] Policy makers' and the industries' critique of the nodal pricing design is summarized, for example, by Alaywan et al. (2004), de Vries et al. (2009), Leuthold et al. (2008), Oggioni and Smeers (2012) and Stoft (1997).

compensation schemes have no direct influence on the cleared zonal prices, but indirectly the details of the design may influence how producers make their offers.

The simplest redispatch is exercised as a command and control scheme: the system operator orders adjustments without referring to the market and all agents are compensated for the estimated cost associated with their adjustments (Krause, 2005). In this paper we instead consider a market oriented redispatch, also called *counter-trading*. This zonal design is used in Britain, in the Nordic countries and it was used in the old Texas design.[5] In these markets a producer's adjustments are compensated in accordance with his stated costs as under discriminatory pricing. Thus the market has a zonal price in the first stage and pay-as-bid pricing in the second stage. We consider two cases: a single shot game where the same bid curve is used in both the first and second stage, and a dynamic game where firms are allowed to submit new bid curves in the second stage. The dynamic model is appropriate if, for example, the first stage represents the day-ahead market and the second stage represents the real-time market.

1.1.2. Comparison of the three market designs

Our analysis considers a general electricity network, which could be meshed, where nodes are connected by capacity constrained transmission lines. We study an idealized market where producers' costs are common knowledge, and demand is certain and inelastic. There is a continuum of infinitesimally small producers that choose their offers in order to maximize their individual payoffs.[6] Subject to the transmission constraints, the system operator accepts offers to minimize total stated production costs, i.e. it clears the market under the assumption that offers reflect true costs. We characterize the Nash equilibrium (NE) of each market design and compare prices, payoffs and efficiencies for the three designs.

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[5] Note that Britain is different in that it has pay-as-bid pricing for all accepted bids in the real-time market. The Nordic real-time markets only use discriminatory pricing for redispatches; all other accepted bids are paid a zonal real-time price.

[6] The idea to calculate Nash equilibria for a continuum of agents was first introduced by Aumann (1964). The theory was further developed by Green (1984).

In the nodal pricing design, we show that producers maximize their payoffs by simply bidding their marginal costs. Thus, in this case, the accepted offers do in fact maximize short-run social welfare. We refer to these accepted equilibrium offers as the *efficient dispatch* and we call the clearing prices the *network's competitive nodal prices*. We compare this outcome with equilibria in the alternative market designs.

For fixed offers, the system operator would increase its profit at producers' expense by switching from nodal to discriminatory pricing. But we show that even if there are infinitely many producers in the market, discriminatory pricing encourages strategic bidding among inframarginal production units. They can increase their offer prices up to the marginal price in their node and still be accepted.[7] In the Nash equilibrium of the pay-as-bid design, accepted production is the same as in the efficient dispatch and all accepted offers are at the network's competitive nodal prices. Thus, market efficiency and payoffs to producers and the system operator are the same as for nodal pricing. As payoffs are identical in all circumstances, this also implies that the long-run effects are the same in terms of investment incentives.

Under our idealized assumptions, the zonal market with counter-trading has the same efficient dispatch as in the two other market designs. We also show that producers buy and sell at the competitive nodal price in the counter-trading stage. Still producers' payoffs are larger under zonal pricing at consumers' and the system operator's expense. The reason is that the two-stage clearing gives producers the opportunity to either sell at the zonal price or at the discriminatory equilibrium price in the second stage, whichever is higher. In addition, even when they are not producing any energy, production units in export-constrained nodes can make money by selling at the uniform zonal price and buying back the same amount at the discriminatory price, which is lower, in the second stage. This increase-decrease game has been observed during the California electricity crisis (Alaywan et al., 2004), it destroyed the initial PJM zonal design, and is present in the UK in the form of large payments to Scottish generators

[7] Related results have been found for theoretical and empirical studies of discriminatory auctions (Holmberg and Newbery, 2010; Evans and Green, 2004). However, previous studies of discriminatory pricing have not taken the network into account.

(Neuhoff, Hobbs and Newbery, 2011). Our results show that inc-dec gaming is an arbitrage strategy, which cannot be removed by improving competition in the market. If it is a serious problem, it is necessary to change the market design as in the U.S. We show how producers' profits from the inc-dec game can be calculated for general networks, including meshed networks. Our results for the zonal market are the same for the static game, where the same offer is used in the two stages, and in the dynamic game, where firms are allowed to make new offers in the counter-trading stage.

Additional payments to producers in the zonal market cause long-run inefficiencies; producers overinvest in export-constrained nodes (Dijk and Willems, 2011).[8] Zonal pricing also leads to inefficiencies in the operation of inflexible plants with long ramp-rates, which are not allowed to trade in the real-time market. Related issues are analyzed by Green (2007). In practice nodal pricing is considered superior to the other designs, as it ensures efficient allocation in a competitive market also for uncertain demand and intermittent wind power production; an advantage which is stressed by Green (2010).

The organization of the paper is as follows. In Section 2 we present a simple two–node example illustrating the equilibrium under the nodal pricing. Section 3 discusses our model and in Section 4 we present an analysis of the three congestion management designs. In section 5, market equilibria for the discriminatory and zonal pricing designs are discussed with the means of a simple example. The paper is concluded in section 6, which also briefly discusses how more realistic assumptions would change our results. Three technical lemmas and all proofs are placed in the Appendix.

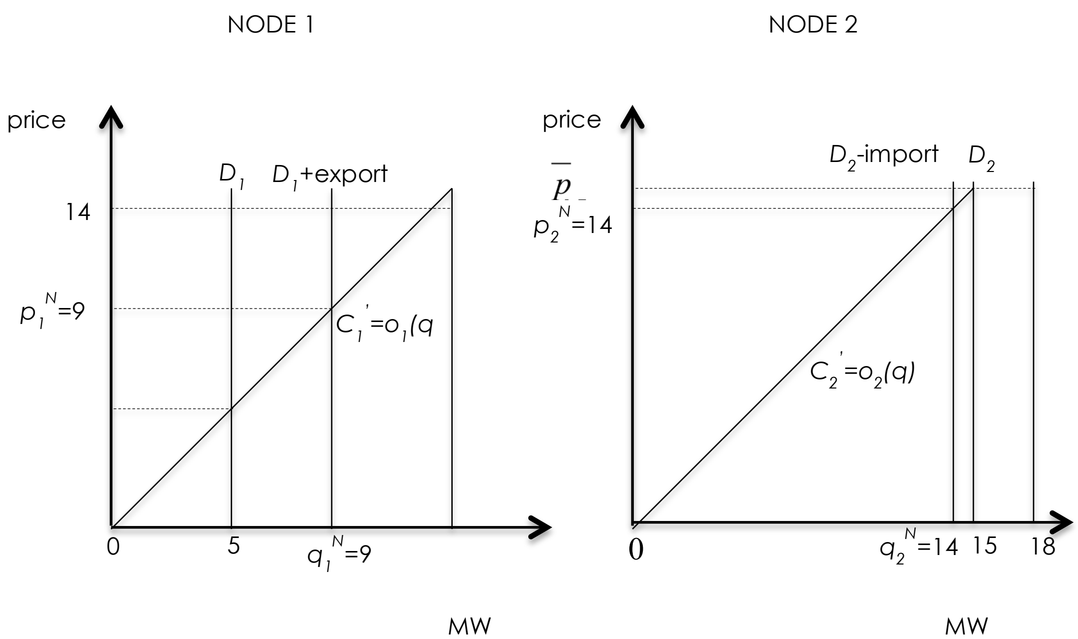
1.2. Example – Nodal pricing

In the following section we describe a simple example of bidding under nodal pricing and the equilibrium outcome of this design. We consider a two-node network with one constrained transmission-line in-between. In

[8] Ruderer and Zöttl (2012) show that zonal pricing in addition leads to inefficient investments in transmission-lines, at least if the zonal market is regulated such that redispatches are compensated according to producers' true costs.

both nodes producers are infinitesimally small and demand is perfectly inelastic. For simplicity, we make the following assumptions for each node: the marginal cost is equal to local output and the production capacity is 15 MW. In node 1, demand is 5 MW; in node 2 demand is 18 MW. The transmission line between these nodes is constrained and can carry only 4 MW. Demand in node 2 exceeds its generation possibilities so the missing electricity must be imported from the other node.

Figure 1. Equilibrium for nodal pricing.



With nodal pricing, the equilibrium offers will be as shown in Fig. 1. In the first node infinitesimally small producers make nodal offers *o(q)* at their marginal cost. In order to satisfy local demand and export, 9 MW are going to be dispatched. Out of these, 5 MW will be consumed locally and 4 MW will be exported; the highest possible export level that the transmission line allows for. The marginal cost and nodal price is equal to 9, which corresponds to the total production of this node. In the second node, the nodal price is 14 as there are 14 MW that have to be produced in the second node in order to satisfy demand and the transmission constraint. Production above those marginal costs (9 in node 1 and 14 in node 2) will not be dispatched. All accepted production will be paid the nodal price of the node. The dispatch leads to a socially efficient outcome. We use the superscript N to designate this outcome. We call nodal production and nodal prices of competitive and socially efficient outcomes, the network's efficient dispatch and the network's competitive nodal prices, respectively.

As our analysis will show, the offers in Figure 1 cannot constitute NE in the other two designs. For discriminatory pricing it will be profitable for inframarginal offers to increase their price up to the marginal offer of the node. For zonal pricing, the average demand in the two zones would be 11.5 MW, so 11.5 MW would be accepted in each node at the zonal price 11.5 for the offers in Figure 1. Production would be adjusted in the redispatch stage. However, as it applies discriminatory pricing, it would not influence the payoff of producers that bid their true marginal cost. Thus, producers in the export-constrained node 1 would find it profitable to change their offers downwards. They would like to sell as much as possible at the zonal price and then buy it back at a lower price in the redispatch stage. Producers in the import-constrained node 2 would shift their offers upwards as in the pay-as-bid design, so that all production that is dispatched in the redispatch stage is accepted at the marginal offer of the import-constrained node.

1.3. Model

The model described in this section is used to evaluate and compare three market oriented congestion management techniques: nodal pricing, pay-as-bid and zonal pricing with counter-trading. We study a general electricity network (possibly meshed) with n nodes that are connected by capacity constrained transmission lines. Demand in a node $i \in \{1,\ldots,n\}$ is given by D_i, which is certain and inelastic up to a reservation price $\overline{p}$. $C'_i(q_i)$ is the marginal cost of producing q_i units of electricity in node i. We assume that the marginal cost is common knowledge, continuous and strictly increasing up to (and beyond) the reservation price.[9] We let $\bar{q}_i > 0$ be the relevant total production capacity in node *i,* which has a marginal cost at the reservation price or lower. Thus we have by construction that $\bar{p} = C'_i(\bar{q}_i)$. Capacity with a marginal cost above the reservation price will not submit any offers.

In each node there is a continuum of infinitesimally small producers. Each producer in the continuum of node *i* is indexed by the variable $g_i \in [0,1]$. For simplicity, we assume that each producer is only active in one node. Without loss of generality, we also assume that producers are sorted with respect to their marginal cost in each node, such that a producer with a higher g_i value than another producer in the same node also has a higher marginal cost. The relevant total production capacity $\bar{q}_i$ in a node *i* is divided between the continuum of producers, such that firm g_i in node *i* has the marginal cost $C'_i(g_i \bar{q}_i)$. Similarly, we let $\hat{o}_i(g_i \bar{q}_i)$ represent the offer price of firm g_i in node *i.*

The system operator's clearing of the real-time market must be such that local net-supply equals local net-exports in each node and such that the physical constraints of the transmission network are not violated. Any set $\{q_i\}_{i=1}^n$ of nodal production that satisfies these feasibility constraints is referred to as a feasible dispatch. We say that a dispatch is locally efficient if it minimizes the local production cost in each node for given nodal outputs $\{q_i\}_{i=1}^n$, i.e. production units in node *i* are running if and only if they have a marginal cost at or below $C'_i(q_i)$. We consider a set of demand outcomes $\{D_i\}_{i=1}^n$, such that there is at least one feasible dispatch. In principle the network could be a non-linear AC system with resistive losses. But to ensure a unique cost efficient dispatch we restrict the analysis to cases where the feasible set of dispatches is convex. Hence, if two dispatches are possible, then any weighted combination of the two dispatches is also feasible. The feasi-

[9] Note that it is possible for a producer to generate beyond the rated power of a production unit. However, it heats up the unit and shortens its lifespan. Thus the marginal cost increases continuously beyond the rated power towards a very high number (above the reservation price) where the unit is certain to be permanently destroyed during the delivery period. Edin (2007) uses a similar marginal cost curve with a similar motivation.

ble set of dispatches is for example convex under the *DC load flow approximation* of general networks with alternating current (Chao and Peck, 1996)[10].

The system operator sorts offers in ascending order in case a nodal offer curve $\hat{o}_i(q_i)$ would be locally decreasing. We denote the sorted nodal offer curve by $o_i(q_i)$. The system operator then chooses a feasible dispatch in order to minimize the stated production cost or equivalently to maximize

$$W = -\sum_{i=1}^{n} \int_0^{q_i} o_i(y)dy \qquad (1)$$

which maximizes social welfare if offers would reflect the true costs. Thus, we say that the system operator acts in order to maximize the *stated social welfare* subject to the feasibility constraints.

In a market with nodal pricing the system operator first chooses the optimal dispatch as explained above. All accepted offers in the same node are paid the same nodal price. The nodal price is determined by the node's marginal price, i.e. the highest accepted offer price in the node. We say that marginal prices or nodal prices are locally competitive if the dispatch is locally efficient and the marginal price in each node equals the highest marginal cost for units that are running in the node. An offer at the marginal price of its node is referred to as a marginal offer. In the discriminatory pricing design all accepted offers are paid according to their offer price. This gives producers incentives to change their offers and thereby state their costs differently. Still, the dispatch is determined in the same way; by minimizing stated production cost. In the zonal pricing design with counter-trading, the market is cleared in two stages. First the system operator clears the market disregarding the intra-zonal transmission constraints (constraints inside zones). Next, in case intra-zonal transmission lines are overloaded after the first clearing, there is a redispatch where the system operator increases accepted production in import constrained nodes and

---

[10] Alternating currents (AC) result in a non-linear model of the network. Hence, in economic studies this model is often simplified by a linear approximation called the *direct current (DC) load flow approximation*. In addition to Chao and Peck (1996), it is used, for example, by Schweppe et al. (1988), Hogan (1992), Bjørndal and Jörnsten (2001, 2005, 2007), Glachant and Pignon (2005), Green (2007) and Adler et al. (2008).

reduces it in export constrained nodes. Section 4.3 explains our zonal pricing model in greater detail.

1.4. Analysis

We start our game-theoretical analysis of the three market designs by means of three technical results that we will use in the proofs that follow.

> **Lemma 1.** Assume that offers are shifted upwards (more expensive) in some nodes and shifted downwards (cheaper) in others, then the dispatched production is weakly lower in at least one node with more expensive offers or weakly higher in at least one node with cheaper supply.

One immediate implication of this lemma is that:

> **Corollary 1** (Non-increasing residual demand) If one producer unilaterally increases/decreases its offer price, then accepted sales in its node cannot increase/decrease.

The system operator accepts offers in order to minimize stated production costs. Thus for a given acceptance volume in a node, a firm cannot increase its chances of being dispatched by increasing its offer price. Thus Corollary 1 implies that a producer's residual demand is non-increasing. The next lemma outlines necessary properties of a Nash equilibrium.

> **Lemma 2.** Consider a market where an accepted offer is never paid more than the marginal price of its node and never less than its own bid price. In Nash equilibrium, the dispatch must be locally efficient and marginal prices of the nodes are locally competitive.

1.4.1. Nodal pricing

Below we prove that the nodal pricing design has at least one NE and that all NE results in the same competitive outcome.[11] It is only offers above and below the marginal prices of nodes that can differ between equilibria.

> **Proposition 1** A market with nodal pricing has one NE where producers offer at their marginal cost. All NE result in the same locally efficient dispatch $\{q_i^N\}_{i=1}^n$ and the same competitive nodal prices $p_i^N = C_i'(q_i^N)$.

As the system operator clears the market in order to maximize social welfare when offers reveal true costs, we note that the equilibrium dispatch must be efficient. We use the superscript *N* to designate this socially efficient outcome. We refer to the unique equilibrium outcome as the network's efficient dispatch $\{q_i^N\}_{i=1}^n$ and the network's competitive nodal prices $\{p_i^N\}_{i=1}^n$. Note that as the dispatch is locally efficient, the unique equilibrium outcome exactly specifies which units are running; production units in node *i* are running if and only if they have a marginal cost at or below $C'_i(q_i^N)$. Schweppe et al. (1988), Chao and Peck (1996) and Hsu (1997) and others outline methods that can be used to calculate efficient dispatches $\{q_i^N\}_{i=1}^n$ for general networks.

Existence of the competitive outcome also indirectly establishes existence of a Walrasian equilibrium, which has previously been proven for ra-

[11] Existence of pure-strategy NE in networks with a finite number of producers is less straightforward. The reason is that a producer in an importing node can find it profitable to deviate from a locally optimal profit maximum by withholding production in order to congest imports and push up the nodal price (Borenstein et al., 2000; Willems, 2002; Downward et al., 2010; Holmberg and Philpott, 2012). Such unilateral deviations are not feasible in a network with infinitesimally small producers, which makes existence of pure-strategy NE more straightforward. Escobar and Jofré (2008) show that networks with a finite number of producers and non-existing pure-strategy NE normally have mixed-strategy NE. Existence of NE in large games with continuous payoffs has been analyzed by Carmona et al. (2009).

dial (Cho, 2003) and meshed networks (Escobar and Jofré, 2008). Proposition 1 proves that all of our NE correspond to the Walrasian equilibrium, so in this sense our NE is equivalent to the Walrasian equilibrium in a market with nodal pricing. The reason is that the infinitesimal producers that we consider are price takers in nodal markets, where all agents in the same node are paid the same market price.

1.4.2. Discriminatory pricing

Discriminatory pricing is different to nodal pricing in that each agent is then paid its individual offer price rather than a uniform nodal price. Thus, even if agents are infinitesimally small, inframarginal producers can still influence how much they are paid, so they are no longer price takers. This means that the Walrasian equilibrium is not a useful equilibrium concept when studying discriminatory pricing. This is the reason why we instead consider a large game with a continuum of small producers in this paper.

> **Proposition 2.** There exist Nash equilibria in a network with discriminatory pricing. All such NE have the following properties:
>
> 1) The dispatched production is identical to the network's efficient dispatch in each node.
>
> 2) All production in node i with a marginal cost at or below $C_i'\left(q_i^N\right)$ is offered at the network's competitive nodal price $p_i^N = C_i'\left(q_i^N\right)$.
>
> 3) Other offers are not accepted and are not uniquely determined in equilibrium. However, it can, for example, be assumed that they offer at their marginal cost.

Thus, the discriminatory auction is identical to nodal pricing in terms of payoffs, efficiency, social welfare and the dispatch. As payoffs are identical for all circumstances, this also implies that the long-run effects are the same in terms of investment incentives etc. Note that it is not necessary that rejected offers bid at marginal cost to ensure an equilibrium. As producers are infinitesimally small, it is enough to have a small finite amount of rejected bids at or just above the marginal offer in each node to avoid deviations.

Finally we analyze how contracts influence the equilibrium outcome. We consider forward contracts with physical delivery in a specific node at a predetermined price. For simplicity, we consider cases where each infinitesimally small producer either has no forward sales at all or sells all of its capacity in the forward market for physical delivery in its own node to consumers. In the real-time market, consumers announce how much more power they want to buy in each node, in addition to what they have already bought with contracts, and producers make offers for changes relative to their contractual obligations. The system operator accepts changes in production in order to achieve a feasible dispatch at the lowest possible net-increase in the stated production costs.

> **Proposition 3.** In a real-time market with nodal or discriminatory pricing, the equilibrium dispatch is identical to the network's efficient dispatch and marginal prices of the nodes are competitive, for any set of forward contracts that producers have sold with physical delivery in their own node.

We will use this result in our analysis of the zonal pricing design, where the first-stage clearing of the zonal market can be regarded as physical forward sales.

1.4.3. Zonal pricing with counter-trading

1.4.3.1. Notation and assumptions

Zonal pricing with counter-trading is more complicated than the other two designs and we need to introduce some additional notation before we start to analyze it. The network is divided into zones, such that each node belongs to some zone k. We let Z_k be a set with all nodes belonging to zone k. To simplify our equations, we number the nodes in a special order. We start with all nodes in zone 1, and then proceed with all nodes in zone 2 etc. Thus, for each zone k, nodes are given numbers in some range $\underline{n}_k$ to

$\bar{n}_k$. Moreover, inside each zone, nodes are sorted with respect to the network's competitive nodal prices p_i^N, which can be calculated for the nodal pricing design, as discussed in Section 4.1. Thus, the cheapest node in zone k is assigned the number $\underline{n}_k$ and the most expensive node in zone k is assigned the number $\bar{n}_k$.

Counter-trading in the second-stage only changes intra-zonal flows. Thus it is important for a benevolent system operator to ensure that the inter-zonal flows are as efficient as possible already after the first clearing. In the Nordic multi-zonal market, system operators achieve this by announcing a narrow range of inter-zonal flows before the day-ahead market opens. In particular, flows in the "wrong direction", from zones with high prices to zones with low prices, due to loop flows, are predetermined by the system operator. We simplify the zonal clearing further by letting the well-informed system operator set all inter-zonal flows before offers are submitted. Total net-imports to zone k are denoted by I_k^N. We make the following assumption for these flows, as our analysis shows that it leads to an efficient outcome:

> **Assumption 1**: The system operator sets inter-zonal flows equal to the inter-zonal flows that would occur for the network's efficient dispatch $\{q_i^N\}_{i=1}^n$. These inter-zonal flows are announced by the system operator before offers are submitted.

Assumption 1 sets all inter-zonal flows. Thus offers to each zonal market can be cleared separately at a price where zonal net-supply equals zonal net-exports. We assume that the highest potential clearing price is chosen in case there are multiple prices where zonal net-supply equals zonal net-exports[12]. The clearing price Π_k in zone k is paid to all production in the zone that is accepted in the zonal clearing. In case intra-zonal transmission-

---

[12] Normally this choice does not matter for our equilibria. However, it ensures existence of equilibria for degenerate cases when exogenous zonal demand and exogenous net-exports happen to coincide with production capacities in one or several nodes for some zone.

lines are overloaded after the first clearing, there is a redispatch where the system operator increases accepted production in import constrained nodes and reduces it in export-constrained nodes. We consider a market oriented redispatch (counter-trading), so all deviations from the first-clearing are settled on a pay-as-bid basis. In the counter-trading stage, the system operator makes changes relative to the zonal clearing in order to achieve a feasible dispatch at the lowest possible net-increase in stated production costs.

We consider two versions of the zonal design: a one shot game where the same offers are used in the two clearing stages of the market and a dynamic game where agents are allowed to make new offers in the counter-trading stage. The first model corresponds to the old pool in England and Wales, while the latter model could for example be representative of the reformed British market, where producers can first sell power at a uniform zonal price in the day-ahead market and then submit a new bid to the real-time market with discriminatory pricing.[13]

1.4.3.2. Analysis

The equilibrium in a zonal market with counter-trading has some similarities with the discriminatory auction. But the zonal case is more complicated, as the two clearing stages imply that in equilibrium some producers can arbitrage between their zonal and individual (discriminatory) counter-trading prices. Thus producers in nodes with low marginal prices will play

[13] The dynamic model could also represent congestion management in the Nordic market, where the system operator does not accept offers in the zonal clearing of the real-time market if these offers will cause intra-zonal congestion that needs to be countertraded in the second-stage. This is to avoid unnecessary costs for the system operator and unnecessary payments to producers. In our model where there is no uncertainty, the zonal day-ahead market then takes the role of the first-stage of the real-time market. The zonal real-time market becomes obsolete as without uncertainty, the day-ahead market has already cleared the zones. In this case offers to the real-time market, which are allowed to differ from day-ahead offers, are only used in the discriminatory counter-trading stage. Proposition 5 shows that under our idealized assumptions switching to the Nordic version of zonal congestion management is in vain, producers still get the same payoffs and the system operator's counter-trading costs are unchanged.

the inc-dec game, i.e. sell all their capacity at the higher zonal price and then buy back the capacity at a lower price in the counter-trading stage or produce if the marginal cost is even lower. We consider physical markets. This prevents producers from buying power or selling more than their production capacity in the zonal market. Thus a producer in a node with a marginal price above its zonal price cannot make an arbitrage profit. To maximize their profit in the redispatch stage, bids of dispatched production in such import constrained nodes are shifted upwards to the node's competitive nodal price, similar to the case with discriminatory pricing.

First we consider a static game where producers cannot make new offers to the counter-trading stage; the same offers are used in the two stages of the zonal market.

> **Proposition 4.** Under Assumption 1 there exists Nash equilibria in a zonal market with counter-trading and the same offers in the zonal and countertrading stages. All of them have the following properties:
>
> 1. The zonal price in zone k is given by $\Pi_k^* = p_{m(k)}^N$, where:
>
> $$m(k) = \begin{cases} n \in \{\underline{n}_k, \ldots, \bar{n}_k\} : I_k^N + \sum_{i=\underline{n}_k}^{n-1} \bar{q}_i \leq \sum_{i=\underline{n}_k}^{\bar{n}_k} D_i < I_k^N + \sum_{i=\underline{n}_k}^{n} \bar{q}_i & \text{if } \sum_{i=\underline{n}_k}^{\bar{n}_k} D_i < I_k^N + \sum_{i=\underline{n}_k}^{\bar{n}_k} \bar{q}_i \\ \bar{n}_k \quad \text{if } \sum_{i=\underline{n}_k}^{\bar{n}_k} D_i = I_k^N + \sum_{i=\underline{n}_k}^{\bar{n}_k} \bar{q}_i & \end{cases}$$
>
> 2. As in the nodal pricing and pay-as-bid designs, the dispatched production in each node is given by the network's efficient dispatch, q_i^N.
>
> 3. In strictly export-constrained nodes $i \in Z_k$, such that $p_i^N <$ Π_k^*, production with marginal costs at or above p_i^N are offered at the network's competitive nodal price $p_i^N = C_i'\left(q_i^N\right)$. For strictly import-constrained nodes in zone k where $p_i^N >$

Π_k^*, all production with a marginal cost at or below $C_i'\left(q_i^N\right)$ is offered at $p_i^N = C_i'\left(q_i^N\right)$.

4. Other offers are not uniquely determined in equilibrium. However, it can be assumed that they offer at their marginal cost.

Equation (2) defines a *marginal node*, where the competitive nodal price equals the zonal price. Next we show that the equilibrium outcome does not change in the dynamic game, where agents are allowed to up-date their offers in the counter-trading stage.

Proposition 5. Under Assumption 1, it does not matter for payoffs or the equilibrium outcome of the zonal market whether producers are allowed to up-date their offers in the counter-trading stage.

We can now conclude that the dispatch for zonal pricing with counter-trading is the same as for nodal pricing and discriminatory pricing. Thus, in the short run, the designs' efficiencies are equivalent. This also confirms that the system operator should set inter-zonal flows equal to the corresponding flows in the competitive nodal market, as assumed in Assumption 1, if it wants to maximize social welfare. However, it directly follows from Equation (2) and Propositions 4 and 5 that producers in strictly export-constrained nodes receive unnecessarily high payments in a zonal pricing design:

Corollary 2. In comparison to nodal pricing, the total extra payoff from the system operator to producers in zone k equals: $\sum_{i=\underline{n}_k}^{m(k)-1}\left(p_{m(k)}^N - p_i^N\right)q_i$ under Assumption 1.

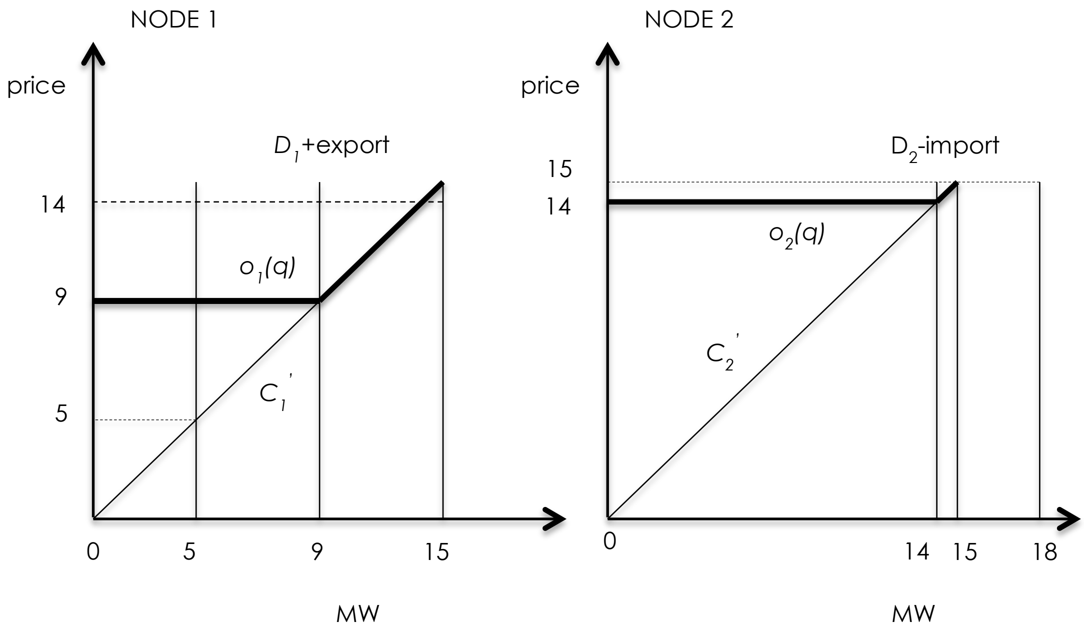
Even if zonal pricing is as efficient as nodal pricing in the short run, the extra payoffs will cause welfare losses in the long run. Production investments will be too high in strictly export-constrained nodes where $p_i^N < \Pi_k$. In addition, inflexible production that cannot take part in the real-time market are paid the zonal price in the day-ahead market. Thus, the accepted inflexible supply in this market is going to be too high in strictly export-constrained nodes and too low in strictly import-constrained nodes.

1.5. Example – discriminatory and zonal pricing

In the following section, we illustrate the equilibria for the discriminatory and zonal pricing designs. The example that we use has an identical structure as the nodal pricing case that we described in section 2. Again, we consider a two-node network with one constrained transmission-line in-between. In both nodes producers are infinitesimally small and demand is perfectly inelastic. In each node the marginal cost is equal to local output and the production capacity is 15 MW. In node 1, demand is 5 MW; in node 2 demand is 18 MW. The transmission line between these nodes is constrained and can carry only 4 MW. Demand in node 2 exceeds its generation possibilities so the missing electricity must be imported from the other node.

The discriminatory design will result in the equilibrium offers presented in Fig. 2. In this design, generators are paid according to their bid. Knowing this and having perfect information, producers who want to be dispatched will bid the competitive nodal price of their node, to ensure that they will be dispatched at the highest possible price. Thus, in node 1, they will bid 9 and in node 2 they will bid 14. Producers who do not want to be dispatched may, for example, bid their marginal costs, which are higher than the nodal prices of the respective nodes. The dispatch will be the same as under nodal pricing design. Although producers will have different bidding strategies in both designs, the overall result will be the same. Accepted production will be paid 9 in node 1 and 14 in node 2.

Figure 2: Equilibrium for discriminatory pricing.



In the zonal design with counter-trading, producers will offer as follows:

Figure 3: Zonal offer in equilibrium for zonal pricing with counter-trading.

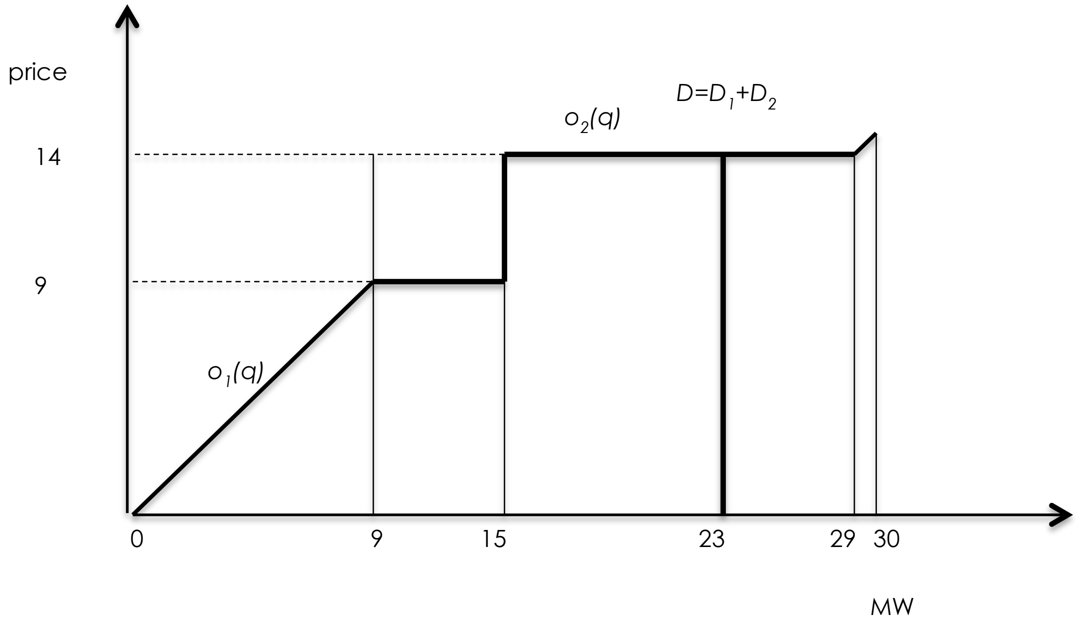
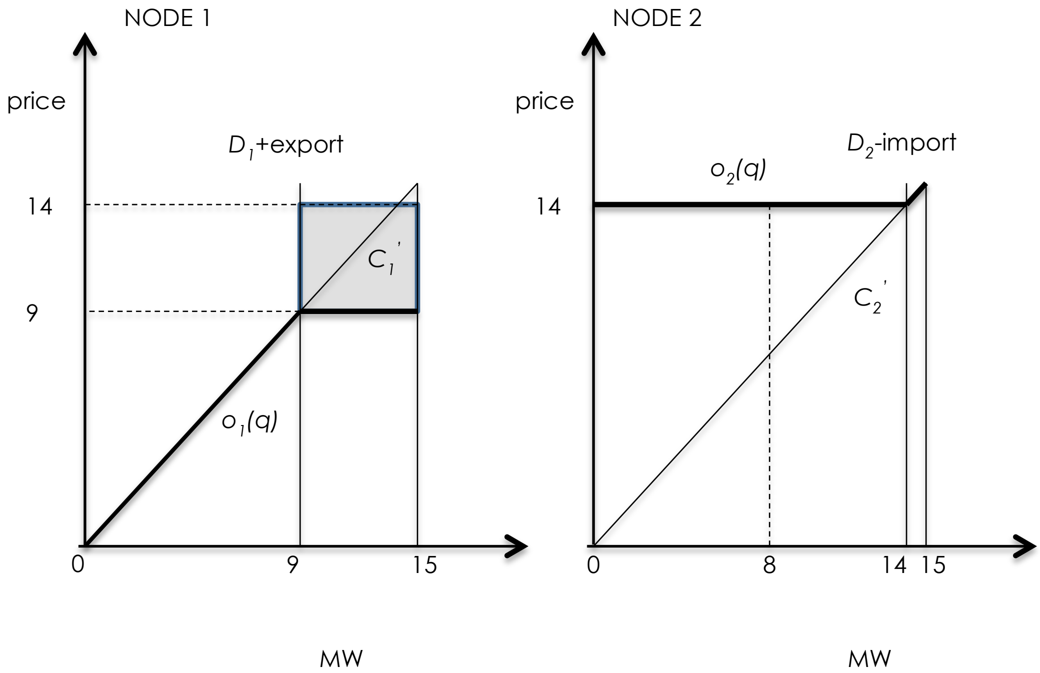


Figure 4: Nodal offers in equilibrium for zonal pricing with counter-trading



Node 1:

Due to transmission constraints, producers in node 1 know that after the two stages, the system operator can accept a maximum of 9 MW in their node. Therefore, producers with a marginal cost at or below the competitive nodal price, offer at or below the competitive nodal price as they will, in any case, be accepted and paid the zonal price, which is 14. The remaining 6 units in node 1 have a marginal cost above the competitive nodal price. They will bid low in order to be accepted in the first stage and be paid the zonal price of 14. But due to the transmission constraint, they will have to buy back their supply at their own bidding price in the second round. As they are interested in maximizing their profit, they want this price difference to be as large as possible, as long as they will not be chosen to produce. Therefore, they bid the competitive nodal price 9 so that they will be "paid" not to produce and get 14 – 9 =5 (the rectangle area in the figure 4). There are no profitable deviations from these bids for producers from node 1. In particular, we note that no infinitesimally small producer in node 1 can unilaterally increase the zonal price at stage 1 above 14, as there are 6 units (in node 2) that offer their production at the price 14 without being accepted in the zonal market.

Node 2:

Due to the transmission constraint, producers in node 2 know that the system operator needs to dispatch at least 14 units of electricity in their node after the two stages. Thus, all low-cost generators who want to be dispatched know that all offers at or below 14, the competitive nodal price of node 2, will be accepted. 8 units are accepted in the zonal clearing and another 6 units are accepted in the counter-trade stage. The latter units are paid as bid and accordingly, they maximize their profit by offering their supply at 14, the highest possible price for which they are going to be accepted. Producers that do not want to be dispatched at all will bid above 14, for example their marginal cost. In this way, 14 units will be produced in node 2. There are no profitable deviations from these strategies for producers in node 2.

A comparison of these two examples and the nodal pricing example in Section 2 illustrates that although the bidding strategies are different, the dispatch is the same in all scenarios. However, the last design – zonal pricing with counter-trading – results in additional payments that affect the long-term investment incentives.

It is interesting to note that the zonal price in our example is weakly higher than the nodal prices in both nodes. This is always the outcome in two-node networks where the production capacity in the cheapest node is not sufficient to meet the total demand, so that it is the marginal cost in the most expensive node that sets the zonal price. The system operator will typically use tariffs to pass its counter-trading cost on to the market participants, so it is actually quite plausible that switching to nodal pricing will lower the cost for all electricity consumers, including the ones in the high cost node.

1.6. Conclusions and discussion

We consider a general electricity network (possibly meshed), where nodes are connected by capacity constrained transmission lines. In our game-theoretical model producers are infinitesimally small and demand is certain and inelastic. We find that the three designs, nodal, zonal with countertrading and discriminatory pricing, lead to the same socially efficient dispatch. In addition, payoffs are identical in the pay-as-bid and nodal pricing designs. However, in the design with zonal pricing and countertrading, there are additional payments from the system operator to producers who can make money by playing the infamous inc-dec game. It does not matter for our results whether we consider a static game where producers' bids are the same in the zonal and counter-trading stages or a dynamic game where producers are allowed to update their offer curves in the counter-trading stage.

Similar to Dijk and Willems' (2011) two-node model, our results for the zonal market imply that producers overinvest in export-constrained nodes. While zonal pricing is good for producers, consumers would gain overall from a switch from zonal to nodal pricing. In two-node markets, it is normally the case that all consumers (also the ones in the most expensive node) would gain from a switch to nodal pricing. In addition to the inefficiencies implied by our model, zonal pricing also leads to inefficiencies in the operation of inflexible plants with long ramp-rates. They are not allowed to trade in the real-time market, so they have to sell at the zonal price in the day-ahead market. The consequence is that too much inflexible production is switched on in export constrained nodes, where the competitive nodal price is below the zonal price, and too little in import constrained nodes, where the competitive nodal price is above the zonal price. Related issues are analyzed by Green (2007).

Another result from our analysis is that there is a significant number of firms that make offers exactly at the marginal prices of the nodes in the zonal and pay-as-bid designs, which is not necessarily the case under nodal pricing. This supports the common view that the zonal design is more liquid. Although, the standard motivation for this is that the zonal design has less market prices and thus fewer products to trade, and hence liquidity can be concentrated on these. Still it is known from PJM that it is also possible to have a liquid market with nodal pricing (Neuhoff and Boyd, 2011).

However increased liquidity can have more drawbacks than advantages. As illustrated by Anderson et al. (2009), the elastic offers, especially in the pay-as-bid design but also in the zonal design, mean that getting its offer slightly wrong can have a huge effect on a firm's dispatch. This increases the chances of getting inefficient dispatches when demand or competitors' output is uncertain, while the efficiency of the nodal pricing design is more robust to these uncertainties. Similarly, Green (2010) stresses the importance of having designs that can accommodate uncertainties from intermittent power.

There are other drawbacks with the zonal design. We consider a benevolent system operator that uses counter-trading to find the socially optimal dispatch. However, even if counter-trading is socially efficient, it is costly for the system operator itself. Thus strategic system operators have incentives to find the feasible dispatch that minimizes counter-trading costs. In practice, counter-trading is therefore likely to be minimalistic and less efficient than in our framework. Moreover, Bjørndal et al. (2003) and Glachant and Pignon (2005) show that network operators have incentives to manipulate inter-zonal flows in order to lower the counter-trading cost (and market efficiency) further. In our analysis we assume that the system-operator has full control of the system and that it can set inter-zonal flow as efficiently as under nodal pricing, but in practice market uncertainty, coordination problems and imperfect regulations lead to significantly less efficient cross-border flows (Leuthold, 2008; Neuhoff, et al., 2011; Ogionni and Smeers 2012). Studies by Hogan (1999), Harvey and Hogan (2000), and Green (2007) indicate that nodal pricing is also better suited to prevent market power.

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Appendix A: Technical lemmas

Lemma 3. m(k) is uniquely defined by Equation (2).

Proof:
We first note that the network's efficient dispatch is feasible as the inter-zonal flows are efficient, i.e. $\sum_{i=\underline{n}_k}^{\bar{n}_k} D_i = I_k^N + \sum_{i=\underline{n}_k}^{\bar{n}_k} q_i^N$. Thus $\sum_{i=\underline{n}_k}^{\bar{n}_k} D_i \le I_k^N + \sum_{i=\underline{n}_k}^{\bar{n}_k} \bar{q}_i$.
We have $m(k) = \bar{n}_k$ if $\sum_{i=\underline{n}_k}^{\bar{n}_k} D_i = I_k^N + \sum_{i=\underline{n}_k}^{\bar{n}_k} \bar{q}_i$.
Otherwise we have $I_k^N + \sum_{i=\underline{n}_k}^{\underline{n}_k - 1} \bar{q}_i < \sum_{i=\underline{n}_k}^{\bar{n}_k} D_i < I_k^N + \sum_{i=\underline{n}_k}^{\bar{n}_k} \bar{q}_i$. Moreover, $I_k^N + \sum_{i=\underline{n}_k}^{n-1} \bar{q}_i$ is strictly increasing in n, because $\bar{q}_i > 0$. Thus Equation (2) always has a unique solution. ■

The following two technical lemmas are used to prove that all Nash equilibria must result in the same dispatch.

Lemma 4. If there is a set of nodal offer functions $\{\hat{o}_i^*(q)\}_{i=1}^n$ (not necessarily increasing) that results in a locally efficient dispatch with the nodal output $\{q_i^*\}_{i=1}^n$ and locally competitive marginal prices, then any set of strictly increasing nodal offer functions $\{\hat{o}_i(q)\}_{i=1}^n$, such that $\hat{o}_i(q_i^*) = \hat{o}_i^*(q_i^*)\ \forall i \in \{1, \ldots, n\}$, will result in the same dispatch.

Proof: First, consider the case when offers $\{\hat{o}_i^*(q)\}_{i=1}^n$ are also strictly increasing in output. In this case, the objective function (stated welfare) is strictly concave in the supply, q_i. Moreover, the set of feasible dispatches is by assumption convex in our model. Thus, it follows that the objective function has a unique local extremum, which is a global maximum (Gravelle and Rees, 1992). Thus the system operator's dispatch can be uniquely determined. It follows from the necessary Lagrange condition that the unique optimum is not influenced by changes in node i's offers below and above the quantity q_i^*, as long as offers are strictly increasing in output. Thus the dispatch must be the same for any set of strictly increasing nodal offer functions $\{\hat{o}_i(q)\}_{i=1}^n$, such that $\hat{o}_i(q_i^*) = \hat{o}_i^*(q_i^*)$ $\forall i \in \{1,\ldots,n\}$.

With perfectly elastic segments in the offer curves $\{o_i^*(q)\}_{i=1}^n$ there are output levels, for which $o_i^{*\prime}(q) = 0$ in some node *i*. This means that the objective function is no longer strictly concave in the supply. However, one can always construct strictly increasing curves that are arbitrarily close to curves with perfectly elastic segments. Moreover, the system operator's objective function is continuous in offers. Thus, we can use the same argument as above with the difference that the system operator may sometimes have multiple optimal dispatches, in addition to the dispatch above, for a given set of offer curves $\{\hat{o}_i^*(q)\}_{i=1}^n$.[14] However, the same dispatch as above is pinned down by the additional conditions that the dispatch is locally efficient and marginal prices locally competitive.

Finally, we realize that there could be cases with non-monotonic offers $\{\hat{o}_i^*(q)\}_{i=1}^n$. However, the dispatch is locally efficient and marginal prices locally competitive, so such offers would have to satisfy the following properties $\hat{o}_i^*(q) \le \hat{o}_i^*(q_i^*)$ for $q \le q_i^*$ and $\hat{o}_i^*(q) \ge \hat{o}_i^*(q_i^*)$ for $q \ge q_i^*$ $\forall i \in \{1,\ldots,n\}$. Thus as the system operator sorts offers into ascending order, we can go through the arguments above for sorted offers and conclude that the statement must hold for such cases as well. ■

> **Lemma 5.** If two sets of nodal offer functions both result in a locally efficient dispatch with locally competitive marginal prices, then the two resulting dispatches must be identical.

Proof: Make the contradictory assumption that there are two pairs of offer functions with a corresponding dispatch, $\left\{\{\hat{o}_i^*(q)\}_{i=1}^n, \{q_i^*\}_{i=1}^n\right\}$ and $\left\{\{\hat{o}_i^\times(q)\}_{i=1}^n, \{q_i^\times\}_{i=1}^n\right\}$, that satisfy the stated properties, except that $\{q_i^*\}_{i=1}^n \neq \{q_i^\times\}_{i=1}^n$.

[14] Multiple optimal dispatches for example occur if several units in a node have the same stated marginal cost and some but not all of these units are accepted in a dispatch that minimizes stated production costs.

Lemma 4 states how these offers can be adjusted into strictly increasing offer curves without changing the dispatch. We make such adjustments to get two sets of adjusted nodal offer functions, $\{\hat{o}_i^*(q)\}_{i=1}^n$ and $\{\hat{o}_i^\times(q)\}_{i=1}^n$ that are identical in nodes with the same dispatch and non-crossing in the other nodes.

By assumption we have $\hat{o}_i^*(q_i^*) = C_i'(q_i^*)$ and $\hat{o}_i^\times(q_i^\times) = C_i'(q_i^\times)$. The node's marginal cost curve is strictly increasing in output. Thus adjusted offers $\{\hat{o}_i^*(q)\}_{i=1}^n$ must be above (more expensive) compared to adjusted offers $\{\hat{o}_i^\times(q)\}_{i=1}^n$ in all nodes where $q_i^* > q_i^\times$. Similarly, adjusted offers $\{\hat{o}_i^*(q)\}_{i=1}^n$ must be below (cheaper) compared to adjusted offers $\{\hat{o}_i^\times(q)\}_{i=1}^n$ in all nodes where $q_i^* < q_i^\times$. However, this would violate Lemma 1. Thus, the dispatches $\{q_i^*\}_{i=1}^n$ and $\{q_i^\times\}_{i=1}^n$ must be identical. ■

Appendix B: Other proofs

Proof of Lemma 1:

We let the *old dispatch* refer to the feasible dispatch $\{q_i^{old}\}_{i=1}^n$ that maximized stated social welfare at old offers when supply in node *i* is given by $o_i(q_i)$. Let $\Delta o_i(q_i)$ denote the shift of the supply curve, so that $o_i(q_i) + \Delta o_i(q_i)$ is the new supply curve in node *i*. The *new dispatch* refers to the feasible dispatch $\{q_i^{new}\}_{i=1}^n$ that maximizes stated social welfare for new offers. Thus for new offers, $o_i(q_i) + \Delta o_i(q_i)$, the new dispatch $\{q_i^{new}\}_{i=1}^n$ should result in a weakly higher social welfare than the old dispatch $\{q_i^{old}\}_{i=1}^n$, i.e.

$$-\sum_{i=1}^n \int_0^{q_i^{new}} (o_i(x) + \Delta o_i(x))dx \geq -\sum_{i=1}^n \int_0^{q_i^{old}} (o_i(x) + \Delta o_i(x))dx. \qquad (3)$$

Now, make the contradictory assumption that in comparison to the old dispatch, the new dispatch has strictly more production in all nodes where offers have been shifted upwards (more expensive) and strictly less production in all nodes where offers have been shifted downwards (cheaper). Thus

$q_i^{new} > q_i^{old}$ when $\Delta o_i(q_i) \geq 0$ with strict inequality for some $q_i \in (0, q_i^{new})$, and $q_i^{new} < q_i^{old}$ when $\Delta o_i(q_i) \leq 0$ with strict inequality for some $q_i \in (0, q_i^{old})$, so that

$$\sum_{i=1}^{n} \int_0^{q_i^{new}} \Delta o_i(x) dx > \sum_{i=1}^{n} \int_0^{q_i^{old}} \Delta o_i(x) dx. \qquad (4)$$

But summing Equation (3) and Equation (4) yields

$$-\sum_{i=1}^{n} \int_0^{q_i^{new}} o_i(x) dx > -\sum_{i=1}^{n} \int_0^{q_i^{old}} o_i(x) dx, \qquad (5)$$

which is a contradiction since, by definition, the old dispatch $\{q_i^{old}\}_{i=1}^{n}$ is supposed to maximize stated welfare at old offers. ■

Proof of Lemma 2:

The statement follows from that: 1) offers cannot be dispatched at a price below their marginal cost in equilibrium, and that 2) all offers from production units with a marginal cost at or below the marginal price of a node must be accepted in equilibrium. If 1) did not hold for some firm then it would be a profitable deviation for the firm to increase its offer price to its marginal cost. 2) follows from that there would otherwise exist some infinitesimally small producer in the node with a marginal cost below the marginal price, but whose offer is not dispatched. Thus, it would be a profitable deviation for such a producer to slightly undercut the marginal price and we know from Corollary 1 that such a deviation will not decrease the dispatched production in its node, so the revised offer will be accepted. ■

Proof of Proposition 1:

We note that the objective function (stated welfare) in Equation (1) is continuous in the nodal output q_i when offers are at the marginal cost. Moreover, the feasible set (the set of possible dispatches) is closed, bounded (because of capacity constraints) and non-empty. Thus, it follows from Weierstrass' theorem that there always exists an optimal feasible dispatch when offers reflect true costs (Gravelle and Rees, 1992).

Next, we note that no producer has a profitable deviation from the competitive outcome. Marginal costs are continuous and strictly increasing. Hence, it follows from Corollary 1 that no producer with an accepted offer can increase its offer price above the marginal price of the node and still be accepted, as its offer price would then be above one of the previously rejected offers in the same node.[15] No producer with a rejected offer would gain by undercutting the marginal price, as the changed offer would then be accepted at a price below its marginal cost. Thus, there must exist an NE where all firms offer to produce at their marginal cost. Offers above and below the marginal price of a node can differ between equilibria. But it follows from Lemma 2 and Lemma 5 in Appendix A that all NE must have the same locally efficient dispatch and the same locally competitive marginal prices, so nodal prices, which are set by marginal prices, must also be the same. ■

Proof of Proposition 2:

Proposition 1 ensures existence of the network's efficient dispatch and competitive nodal prices. Both nodal and discriminatory pricing are markets where an accepted offer is never paid more than its node's marginal price and never less than its own bid price, so in both cases the equilibrium dispatch must be locally efficient and marginal prices of the nodes are competitive in equilibrium, because of Lemma 2. Thus, statement 1) follows from Lemma 5 in Appendix A. In a discriminatory market it is profitable for a producer to increase the price of an accepted offer until it reaches the marginal price of its node, which gives statement 2). Finally, we realise that there are no profitable deviations from the stated equilibrium if rejected offers are at their marginal cost.■

Proof of Proposition 3:

We note that the stated production cost of contracted sales is a constant. Thus we can add it to the objective function of the system operator's optimization problem without influencing the optimal dispatch. The set of feasible dispatches is not influenced by producers' forward sales. Thus to solve for the optimal dispatch we can add producers' forward sales to their offered quantities, so that offers include contracted quantities instead of being net of contracts, and then solve for the feasible dispatch that minimizes the total stated production costs as defined by Equation (1). Rewriting the dis-

[15] Also note that the last unit in a node cannot increase its offer above its marginal cost due to the reservation price $\bar{p} = C'\left(\bar{q}_i\right)$.

patch problem in this way, implies that Lemma 1, Corollary 1, Lemma 4 and Lemma 5 in Appendix A also apply to situations with contracts. Thus, the stated result would follow if we can prove that the dispatch must be locally efficient and marginal prices of the nodes are competitive in equilibrium, also for contracts. Similar to the proof of Lemma 2, this follows from that: 1) a production unit cannot be dispatched at a real-time price below its marginal cost in equilibrium, and that 2) all production units with a marginal cost at or below the marginal real-time price of its node must be dispatched in equilibrium. The proof of Lemma 2 explains why 1) must hold for uncontracted firms. If 1) would not hold for a contracted firm, then it would be a profitable deviation for the firm to increase its offer price (to buy back the contract and avoid being dispatched) to a price above the marginal real-time price and below its marginal cost. It follows from Corollary 1 that such a unilateral deviation cannot increase the nodal production in the contracted firm's node. Thus, its offer to buy back the contract is accepted at a price below its marginal cost, which is cheaper than to follow the contracted obligation and produce at marginal cost. 2) follows from that there would otherwise exist some infinitesimally small producer in the node with a marginal cost below the marginal price, but whose offer is not dispatched. We already know from the proof of Lemma 2 that such a producer would find a profitable deviation if it was uncontracted. We also realize that a producer that has sold its production forward and that has a marginal cost below the marginal price would lose from bidding above the marginal price (to buy back the contract), so that its unit is not dispatched. It would be a profitable deviation for such a producer to lower its bid to its marginal cost. It follows from Corollary 1 that such a change would not decrease accepted production. Thus, it increases its payoff by at least the difference between its nodal marginal price and its marginal cost. ■

Proof of Proposition 4:

Existence of a competitive equilibrium in the nodal design follows from Proposition 1. Assumption 1 restricts inter-zonal flows to be efficient. However, we realize from the proof of Proposition 3 that this extra constraint does not change the statement in Proposition 3. A producer's accepted offer in the zonal market is equivalent to a forward position with physical delivery in its node. Thus it follows from Proposition 3 that, independent of the zonal clearing, the equilibrium dispatch is identical to the network's efficient dispatch and marginal prices of the nodes are competitive in the counter-trading stage. This gives the unique dispatch $\{q_i^N\}_{i=1}^n$ as stated in 2). The counter-trading stage uses discriminatory pricing, but all agents want to trade at the best price possible, so all accepted offers in the counter-trading stage are marginal offers at the network's competitive nodal prices.

Consider a zone *k* with its associated nodes $n \in Z_k$ or equivalently $n \in \{\underline{n}_k, \ldots, \bar{n}_k\}$. A node inside zone *k* where the network's competitive nodal price p_i^N is strictly below the zonal price Π_k is referred to as a strictly export constrained node. Price-taking producers in such nodes want to sell as much production as they can at the zonal price, and then buy back production in the discriminatory counter-trading stage at the lower price p_i^N or produce at an even lower marginal cost. Thus all capacity in a strictly export constrained node *i* is offered at or below $p_i^N < \Pi_k$. As the real-time market is physical, producers in strictly import-constrained nodes of zone *k* (where the network's competitive nodal price p_i^N is strictly above the zonal price Π_k) are not allowed to first buy power at a low price in the zonal market and then sell power at p_i^N in the counter-trading stage. Thus they neither buy nor sell any power in the zonal market, so they make offers above Π_k. We can conclude from the above reasoning that a marginal offer at the zonal price cannot come from a production unit that is located in a node that is strictly export or import constrained. In equilibrium there must be at least one marginal node *m* with $p_m^N = \Pi_k$. Recall that nodes have been sorted with respect to competitive nodal prices and that that the highest clearing price is chosen in case there are multiple prices where zonal net-supply equals zonal net-exports. Thus, we can define one marginal node by Equation (2)[16]. It follows from Lemma 3 that this equation uniquely sets the zonal price $\Pi_k = p^N_{m(k)}$.

Offers in strictly import constrained nodes, which are above the zonal price, are never accepted in the first stage of the zonal market. For these nodes, it is the rules of the counter-trading stage that determine optimal offer strategies. Thus, the auction works as a discriminatory auction, and we can use the same arguments as in Proposition 2 and Proposition 3 to prove the second part of statement 3).

Production units in a strictly export-constrained node that have a higher marginal cost than their competitive nodal price can sell their power in the zonal market at the zonal price and then buy it back at a lower offer price in the counter-trade stage. Thus, to maximize profits this power is offered at the lowest possible price, for which offers are not dispatched, i.e. at the marginal price of the node. This gives the first part of statement 3). Non-dispatched production units would not gain by undercutting the marginal price. Offers that are dispatched in strictly export-constrained nodes are paid the zonal price. It is not possible for one of these units to increase its offer price above $p_i^N < \Pi_k$ and still be dispatched, as non-dispatched units in such nodes offer at p_i^N. Moreover, it is weakly cheaper for dispatched units to produce instead of buying back power at p_i^N. Thus, they do not have any profitable deviations. Accordingly, the stated offers must constitute a Nash equilibrium. ■

Proof of Proposition 5:

We solve the two-stage game by backward induction. Thus we start by analysing the countertrading stage. A producer's accepted offer in the zonal market is equivalent to a forward position with physical delivery in its node.

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[16] It is possible that nodes with numbers adjacent to *m(k)* have the same competitive nodal prices as node *m(k)*, but it will not change the analysis. It is enough to find one marginal node to determine the zonal price. As an example, it follows from Proposition 1 and our cost assumptions that in the special case when zonal demand equals the zonal production capacity plus efficient imports, then the competitive nodal price equals the price cap in all nodes. Thus any node could be chosen to be the marginal node, but $\bar{n}_k$ is the most natural extension of the first part of Equation (2).

Thus it follows from Proposition 3 that, independent of the zonal clearing, the equilibrium dispatch is identical to the network's efficient dispatch and marginal prices of the nodes are competitive in the counter-trading stage. The counter-trading stage uses discriminatory pricing, but all agents want to trade at the best price possible, so all accepted offers in the counter-trading stage are marginal offers at the network's competitive nodal prices.

We calculate a subgame perfect Nash equilibrium of the game, so rational agents realise what the outcome of the second-stage is going to be, and make offers to the zonal market in order to maximize profits. Thus, similar to the one-stage game, all production capacity in strictly export-constrained nodes $i \in Z_k$, such that $p_i^N < \Pi_k$, is sold at the zonal price. As before, production capacity in strictly import constrained nodes maximize their payoff by selling no power in the zonal market; all production that is dispatched in strictly import constrained nodes is accepted in the counter-trading stage. As in the one-stage game, the zonal price in zone *k* must be set by the marginal price of some marginal node *m* as defined in Equation (2). Otherwise there must be some offer to the zonal market from a production unit in a strictly export constrained node (with $p_i^N < \Pi_k$) that is rejected, and which would find it profitable to slightly undercut the zonal price. All production units that are dispatched in marginal nodes are sold at the zonal price. As in the one-stage game, there are always rejected offers from units in marginal nodes that can be placed at or just above the zonal price. This rules out that profitable deviations for production units in marginal nodes. Thus all agents get the same payoffs as the game in Proposition 4, where the same offers were used in the zonal and countertrading stages. ■

Chapter 2

Market-specific news and its impact on forward premia on electricity markets*

Abstract: This paper studies the impact of market-specific news on the short-term forward premia on the Nordic electricity market. I show that the short-term premia between the day-ahead and intra-day electricity prices on the Nordic market can be partly explained by the arrival of news specific to the power market. By exploring the types of news, I show that production failures are most important in shaping premia. Production disruptions in coal-powered units are most frequent and have the greatest effect on the differences between the day-ahead and intra-day prices.

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* I am grateful for helpful comments from Richard Friberg, Chloe le Coq, Harry-Paul Vander Elst, Endre Tvinnereim, Nils von der Fehr, two anonymous referees, seminar participants at the Stockholm School of Economics and conference participants at BEEER 2013 in Bergen. Special thanks to Nils Carlson for his help with data and an introduction to Python. This research was financed within the IFN research program *The Economics of Electricity Markets*.

2.1. Introduction

Electricity is an important commodity and input for many firms. Since it cannot be economically stored, firms mitigate price volatility by engaging in the trade of electricity contracts on futures markets. Unexpectedly large spikes in electricity prices can be particularly damaging to industrial consumers and electricity retail companies. Consequently, it is important to understand the price-adjustment process in markets at different horizons and the nature of the shocks that influence these prices.

This paper examines the impact that market-specific news has on the price difference between the day-ahead and the intra-day Nordic electricity market. In Nord Pool (the electricity market of the Nordic countries) market participants (MPs) have an obligation to inform about special events impacting production, consumption and transmission through a channel called Urgent Market Messages (UMMs). I select messages informing about unplanned outages that were issued in between bidding-periods for the two markets and I verify how different types of messages impact electricity prices. I also investigate the effect that an additional 100 MW outage has on the prices. The analysis is based on hourly price data covering the period from the 1st of January 2006 to the 31st of December 2009.

Several papers indicate that future prices are not unbiased predictors of future spot prices of electricity.[17] One explanation of this pattern is explored by Bessembinder and Lemmon (2002), henceforth BL, and has become the most common theoretical foundation for the study of forward premia on electricity markets. The model describes a market in which identical electricity producers and electricity retailers, who are interested in maximizing their respective profits, participate in the futures market in order to hedge their positions. According to BL's model, the difference between the future price and the expected spot price in such an environment will negatively depend on the underlying spot price volatility and positively on the skewness of the price. These results suggest that spot price variance, along with the possibility of price spikes that emerges from the convexity of the

[17] Longstaff and Wang (2004), Douglas and Popova (2008), Hadsell and Shawky (2006), Karakatsani and Bunn (2005), Redl et al. (2009), Botterud et al. (2010).

power production function, are key elements for understanding the forward premium. Although the BL article does explain an important phenomenon about the relation of prices obtained for the same product at markets of different length, it does not explicitly incorporate the effect that new, last-minute information has on the price discovery process.

I propose an explanation of premia that explicitly accounts for information that becomes known after the price on the future market is known but before the spot price has been established. This method enables me to predict the spot price deviation from the future price with the use of the distribution of the spot price until the last-known moment and the last-minute information.

Verifying the impact of public information on prices can be problematic since in practice it might be difficult to distinguish valid information that has impact on price from noise.[18] Fifty-five percent (55%) of all reported UMMs are due to production or consumption failures, or problems on the transmission grid. A further 35% inform about planned maintenance; this is equivalent to a decrease in available capacity due to a shutdown of a plant. The arrival of this news changes market participants' information set and this in turn may be responsible for the emergence of price differences between the intra-day and day-ahead markets.

I use this unique dataset to examine the effect information has on the existence of price differences between the intra-day and day-ahead electricity markets. The intra-day electricity markets, although currently not that liquid, are growing, as there is more intermittent power that due to its irregular nature is traded closer to the real time. The advantage of using the UMM data is that they provide a rich information structure in a clear-cut

[18] Melvin and Yin (2000) study high frequency deutschmark/dollar and yen/dollar quotes; they remove from the news dataset all information not directly related to the United States, Germany or Japan in order to clear a very noisy series. In Berry and Howe (1994) the data used come from Reuter's News – preselected information that is believed to be of interest to the customers of the service and to impact their economic decisions.

setup – all information is likely to be relevant for electricity prices as it reports on the electric power network events. [19]

I show that short time premia exist on Nord Pool and that they are consistent with results obtained from the analysis of other markets. [20] Moreover, I show that the arrival of market news in the time between the bidding for the day-ahead and intra-day markets has an important impact on premia. A more detailed analysis of the messages reveals that fuel used by generators reporting news is also of importance. To the best of my knowledge this is the first study of premia that explicitly takes into account problems on the grid and therefore provides a better understanding of changes in market fundamentals and of the consequences they have on prices.

The topic takes on additional interest as the European Commission is introducing a new set of regulations on submission and publication of data in electricity markets (SPDEM) [21] accompanied by the rules on wholesale energy market integrity and transparency (REMIT). [22] These rules require public disclosure of detailed information concerning, for example, changes to transmission, generation or consumption that are larger than 100 MW

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[19] For example, finance literature uses either pre-scheduled info or non-scheduled news; however, in the latter case it might be difficult to judge which news items are relevant to market performance. Examples of pre-scheduled news analysis can be found in e.g. Evans and Lyons (2005), Ederington and Lee (1993) or Andersen and Bollerslev (1998). Berry and Howe (1994) and Melvin and Yin (2000) are examples of studies of non-scheduled news. Bauwens et al. (2005) is an example of a study that uses both scheduled and non-scheduled news.

[20] Premia on electricity markets have been well documented: Pennsylvania, New Jersey, Maryland (PJM) by Longstaff and Wang (2004) and Douglas and Popova (2008); the New York market (NYISO) by Hadsell and Shawky (2006); the British market by Karakatsani and Bunn (2005); the Nordic market by Redl et al. (2009) and Botterud et al. (2010).

[21] EU 2011b, Regulation (EU) No 1227/2011 of the European Parliament and of the Council of 25 October 2011 on wholesale energy market integrity and transparency, Official Journal of the European Union L 361, 8th December 2011

[22] EU 2013, Draft Regulation on Submission and Publication of Data in Electricity Markets and Amending Annex I to Regulation (EC) No 714/2009 of the European Parliament and of the Council, European Commission, 2013.

and last for longer than "one market time unit," i.e., one hour for the Nord Pool. This increased transparency raises multiple concerns as to how it might impact the behaviour of market players and trading. This analysis contributes to the discussion of REMIT, analysing the impact of publicly available news describing conditions on the power grid on short time premia in the Nordic electricity market.

This paper has seven sections. In the following section I describe the model of BL, who proposed a theoretical foundation for the forward premia in the case of electricity markets. The next section provides a description of the Nordic electricity market. A description of the dataset can be found in Section 4. Section 5 presents the analysis of the premia and of the impact different news has on the prices. Section 6 discusses results and the last section concludes.

2.2. Forward premia in electricity markets

A theoretical framework for studying forward premia in electricity markets has been introduced by BL, who show that in electricity markets the forward price will be a biased forecast of the spot price. They explain the premia through the moments of the spot price distribution.

They set up an equilibrium model that assumes that the power companies are able to forecast the demand with high precision and participate in the spot market at known prices. The power generators are identical and risk-averse and the same applies to electricity consumers, who are also identical and risk-averse. These market participants trade on the spot market and use the futures market to hedge their risk. Both parties use future contracts as hedges to help maximize their objective profit functions. In the model, the forward premium fluctuates in order to maintain the equilibrium between supply and demand for forward contracts. The electricity consumers, in order to avoid losses, react to increased spot price skewness and demand more forward contracts; this drives the forward price up (relative to the expected spot price) and increases the forward premium. On the other hand, increased variance of the spot price reduces retailers' net risk, thus reducing their demand for forward contracts. The model leads to the following relationship:

$$Premium_t = \theta + \sigma_1 Var_t + \sigma_2 Skew_t + \mu_t \tag{1}$$

where variance and skewness of the spot price explain the premium.

The theoretical model presented in BL has subsequently been tested on different electricity markets and different time horizons – Pennsylvania, New Jersey, Maryland (PJM) by Longstaff and Wang (2004) and Douglas and Popova (2008); the New York market (NYISO) by Hadsell and Shawky (2006); the British market by Karakatsani and Bunn (2005); the Nordic market by Redl et al. (2009) and Botterud et al. (2010).

The evidence from this literature supports the theoretical results obtained by BL. The BL model has been subsequently expanded through inclusion of additional variables that might impact the premia. Douglas and Popova (2008) argue that although electricity cannot be stored, the underlying fuel often can, and they estimate a refined model of forward premia in which they include natural gas storage facilities. An explanation of forward premia through market fundamentals also appears in Karakatsani and Bunn's (2005) study. As the most influential factors of forward premia, they identify excess capacity on the previous day, spot volatility on the previous day and spread on previous and current day. Botterud et al. (2010) study a hydro-dominated power system and therefore they include reservoir levels and deviations in inflow while investigating the structure of future premia. However, not only supply-side characteristics can determine premia and Ullrich (2007) expands the BL model by including excess capacity that is defined as the level of available supply in excess of contemporaneous demand. Other aspects that influence the premia include risk measures. Longstaff and Wang (2004) account for price, quantity and revenue uncertainty and show that premia reflect compensation for risk-taking.

2.3. The Nordic day-ahead and intra-day electricity markets

The Nordic electricity market was one of the first deregulated electricity markets in the world and is the largest European electricity market both in turnover and geographical area. It consists of seven countries belonging to the Nordic and Baltic region: Sweden, Norway, Finland, Denmark, Lithuania, Estonia and Latvia.[23] The market is also connected with other countries, e.g., Germany, Poland and the UK. It consists of physical and financial markets. Two physical markets form the Nord Pool Spot and enable trading with the horizon of one day on the day-ahead market Elspot, and between 1 and 36 hours before the delivery of electricity on the intraday market Elbas. Seventy-seven percent (77%) of the total consumption of electrical energy in the Nordic market in 2012 was traded through the Nord Pool Spot. In 2012[24] the total traded volume on Nord Pool reached 432 TWh.[25] Out of this, 334 TWh were traded on Elspot, which was a 13% increase as compared with the volume traded in 2011. The intra-day market is much smaller than the day-ahead. It is a complementary market to the Elspot and handles only around 1% of electricity as compared with the day-ahead market, but it is constantly growing as more wind generation is entering the market. In 2010[26] Elbas's turnover was slightly above 2 TWh, rising to 2.5 TWh in 2011 and reaching 3.2 TWh in 2012.

The "main arena" for electricity trading is the day-ahead market; based on bids and offers a unique price is determined that clears the market for each hour – the system price. However, in case of congestion, the market splits into different price zones. Zones differ in size: Norway, Denmark and, from the end of 2011, Sweden split into several pre-defined zones while Finland and the Baltic operate as one zone each. The functioning of

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[23] http://www.nordpoolspot.com/How-does-it-work/Bidding-areas/

[24] http://www.nordpoolspot.com/Global/Download%20Center/Annual-report/annual-report_Nord-Pool-Spot_2012.pdf

[25] This is including the day-ahead auction at N2EX in the UK.

[26] http://www.nordpoolspot.com/Global/Download%20Center/Annual-report/annual-report_Nord-Pool-Spot_2012.pdf

the intra-day market is somewhat different. The bidding into the Nordic intra-day market is continuous; it starts two hours after the day-ahead market closes and finishes one hour prior to delivery. The bids and offers are settled as soon as the offer meets demand and the range of prices obtained for the same product (electricity traded at a particular hour) can vary from 769.6€/MWh to 0.1€/MWh. It is important to notice that bidding in the day-ahead and the intra-day markets is not without costs. However the cost is small and only marginally larger for the intra-day market than the day-ahead market. The variable cost of placing a 1 MWh bid in the day-ahead market is 0.035€ and 0.08€ in the intra-day market.

The emergence of price zones decreases the importance of the system price in the day-ahead market. The system price is used as a reference for the financial market but is rarely used for real trading; instead, zonal prices are used. In this study I concentrate on the analysis of premia faced by market participants who operate in one of the zones – Sweden.

There are 370 companies from 20 countries trading on Nord Pool.[27] However, in the zones the market concentration is relatively high. In Sweden 80%[28] of electricity is supplied by three biggest companies: Vattenfall, E.ON and Fortum. The concentration ratios measured with the Herfindahl-Hirschman index (HHI) indicate that market is relatively concentrated. The HHI value for Sweden alone is 1,989. Inclusion of other Nordic countries, Finland, Denmark and Norway, decreases the ratio, but it is still above 1,000.[29,30]

There are 29 power plants larger than 100 MW in Sweden.[31] I summarize their characteristics in Table 1.

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[27] Data from 2012 Nord Pool's yearly rapport.

[28] http://ec.europa.eu/energy/energy_policy/doc/factsheets/market/market_se_en.pdf

[29] In Europe markets thought to be moderately concentrated have HHI values between 1,000 and 2,000.

[30] http://www.energimarknadsinspektionen.se/Documents/Publikationer/rapporter_och_pm/ Rapporter%202013/Ei_R2013_12.pdf

[31] State on the 4th of December 2012. Source: http://www.nordpoolspot com/Global/Download%20Center/TSO/Generation-capacity_Sweden_larger-than-100MW-per-unit_06122013.pdf recovered on the 11th of November 2013.

Table 1. Summary characteristics of Swedish electricity production

Areas	*Number of power plants*	*Number of units*	*Main fuel*	*Installed capacity in MW*	*Average size of a unit*
SE1 Luleå	12	21	Hydro	3,764	170.86
SE2 Sundsvall	2	5	Hydro	705	141
SE3	12	24	Oil	1,313	218
Stockholm			Bio	226	113
			Coal	322	161
			Nuclear	9,395	939.5
			Gas	260	260
SE4 Malmö	3	6	Oil	1,005	335
			Bio	126	126
			Gas	450	450
Total: Sweden	29	56		17,566	313.88

Note: State as on the 4th of December 2012; Source: based on data recovered by author from http://www.nordpoolspot.com[32]

Power plants are spread unequally across Sweden. Hydro-fuelled production is based in the northern part of the country in the region of Lulea and Sundsvall. It is the southern part of Sweden that is more diversified and where the marginal type of energy production oil, gas and coal is located.

2.4. Data

2.4.1. Price data

In this analysis I use intra-day and day-ahead hourly prices for electricity traded on Nord Pool from the 1st of January 2006 until the 31st of December 2009. These data are available upon request from the Nord Pool FTP server. I sort the data into 24 time series, each representing a different hour. In the following analysis I consider the average of the Swedish day-

[32] Based on the data from: http://www.nordpoolspot.com/Global/Download%20Center/TSO/Generation-capacity_Sweden_larger-than%20100MW-per-unit_04122012.pdf , recovered on the 11th of November 2013.

ahead prices[33] and the average intra-day prices for the whole market,[34] as these are not available at a more disaggregated level. The intra-day price is an average of the prices obtained for electricity for a particular hour. It covers all trades for the particular product.[35] It does not include any time constraints for when the trade took place as long as the traded product was the same.

Figures 1a and 1b show the evolution of the Swedish day-ahead price and the average intra-day price during the analysed period 2006 – 2010. A huge spike is visible in Figure 1a, when the Swedish day-ahead price reached 1,400€/MWh. The main reason for the increase was an outage of 1,000 MW at the Swedish Ringhals nuclear power plant.[36] Inspection of the intra-day and the day-ahead price figures as well as the Dickey-Fuller test for unit root indicates that the series are stationary.

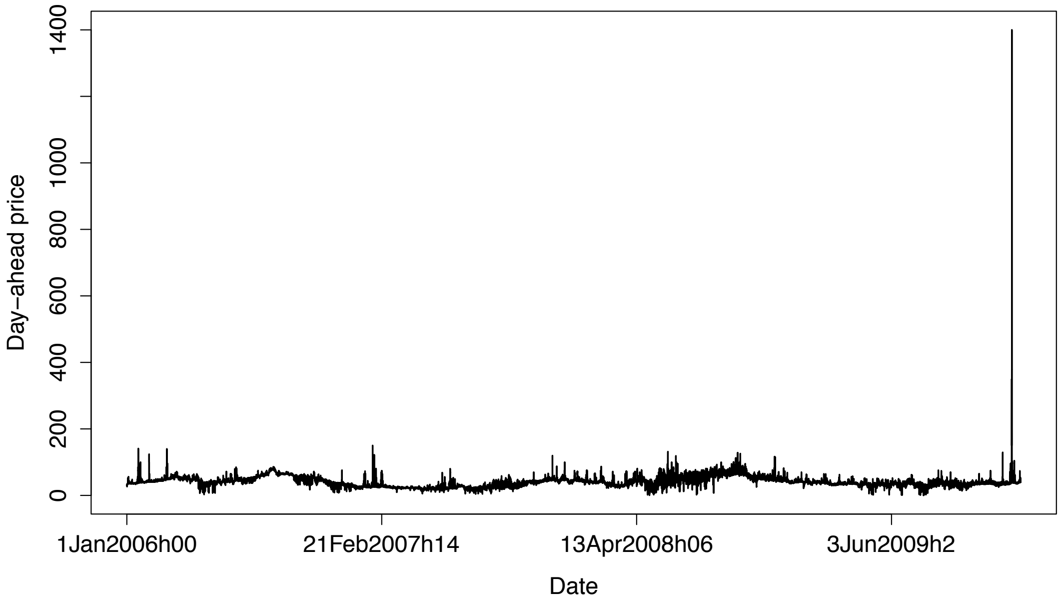
[33] In the analysed period 2006 – 2009, Sweden was one of the 13 zones in the Nord Pool. Sweden has been divided into four separate zones since autumn 2011. http://www.nordpoolspot.com/How-does-it-work/Bidding-areas/Bidding-areas/

[34] Initially it covered only Sweden and then it grew to include other zones of the Nordic market. Therefore, the Elbas series from 1st January 2006 to 10th October 2006 covered only Sweden and Finland and from 19th October 2006 to 31st December 2009 also Denmark and the Kontek area.

[35] The intra-day market functions as a continuous discriminatory auction as opposed to the day-ahead market, which is a uniform auction.

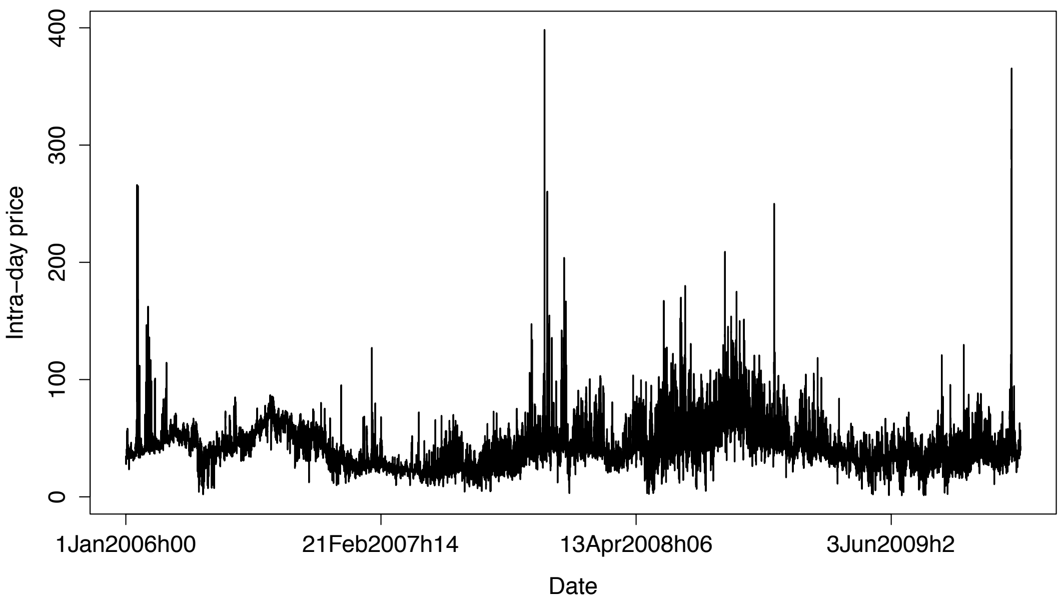
[36] http://nps.makingsoftware.pl/Message-center-container/Exchange-list/Exchange-information/No-1082009-Price-levels-for-the-Elspot-market-on-17-December/

Figure 1a. Day-ahead price over time



Note: This figure shows the evolution of the hourly electricity price on the Nordic day-ahead market from the 1st of January 2006 until the end of December 2009.

Figure 1b. Intra-day price over time



Note: This figure shows the evolution of the electricity price on the Nordic intra-day market from the 1st of January 2006 until the end of December 2009. The intra-day price is an average of the prices obtained for electricity for a particular hour. It covers all trades for the particular product. It does not include any time constraints for when the trade took place as long as the traded product was the same.

Table 2a reports chosen summary statistics for the intra-day and the day-ahead electricity prices. All prices are quoted in Euros per megawatt hour (€/MWh). Hour 1 reports prices of electricity that was sold from 01:00 to 01:59 and Hour 23 from 23:00 to 23:59. As shown in the Table 2a, the average prices for electricity sold day-ahead and intra-day vary throughout the day. In the early morning day-ahead prices are higher than the intra-day, but this relationship is reversed during the rest of the day. It is interesting to note that the day-ahead maximum prices can reach very high levels, while the intra-day prices do not seem to be as high. This however, is due to the fact that intra-day data used in this analysis are average data.

The intra-day and the day-ahead auction-formats differ. The latter is a uniform auction while the former is a continuous discriminatory auction. Market participants do not encounter one average intra-day price while placing their bids, but a range of prices. Table 2b shows detailed information about intra-day prices. The *High price* indicates the highest price that the electricity was sold for, the *Low price* is the lowest price and the *Range* of prices is defined as the difference between the highest and the lowest price over the whole sample. The minimum difference is 0, which indicates that there was just one trade on the intra-day market for the electricity delivered at the particular hour. The maximum difference between prices for the electricity delivered at the same hour reached over 700€/MWh.

Table 2a. Descriptive statistics of the intra-day and the day-ahead prices, Nord Pool 2006 – 2009

Intra-day price	Mean	Std. Dev.	Min.	Max.	Day-ahead price	Mean	Std. Dev.	Min.	Max.
Hour 1	35.42	12.38	2.29	73.84	Hour 1	36.78	12.83	1.88	78.34
Hour 2	33.62	12.35	1.32	73.77	Hour 2	35.20	13.00	0.06	78.15
Hour 15	44.76	18.29	5.43	287.76	Hour 15	43.25	17.06	4.82	379.3
Hour 16	45.14	19.13	13.66	313.7	Hour 16	44.13	38.39	5.45	1400
Hour 17	48.28	23.12	14.15	398.27	Hour 17	45.44	38.73	6.44	1400.1
Hour 18	48.16	20.56	7.32	263.32	Hour 18	44.37	14.71	7.07	200.01
Hour 19	45.99	16.61	7.24	123.71	Hour 19	43.67	14.52	6.69	145.01
Hour 20	44.04	15.30	7.75	128.03	Hour 20	42.68	13.99	7.01	100.26

Notes: This table presents summary statistics for the intra-day and day-ahead electricity prices on the Nordic electricity market Nord Pool during the period from 1st of January 2006 to 31st December 2009. Prices are reported in Euros per megawatt hour. The day-ahead price is the Swedish price.

Table 2b. Summary statistics describing the intra-day prices, Nord Pool 2006 – 2009

Variable	*Obs.*	*Mean*	*Std. Dev.*	*Min.*	*Max.*
Range	35,064	10.82	16.49	0	769.6
High price	35,064	48.64	23.92	1.8	820
Low price	35,064	37.82	15.13	0.1	250
Average	35,064	42.82	18.06	1.23	398.27

Notes: The High price indicates the highest price that the electricity for a particular hour was sold for, the Low price is the lowest price and the Range of prices is defined as the difference between the highest and the lowest price over the whole sample. The dataset consists of hourly observations from Nord Pool (the Nordic electricity market) for the period from the 1st of January 2006 to the 31st of December 2009.

The data illustrate the right-skewed nature of electricity prices. The maximum day-ahead price reaches (for hour 17) 1,400€/MWh, which is more than 30 times the mean value for this hour. Similar price behaviour (although on a smaller scale) is observed for the intra-day prices where the maximal average price is eight times larger than its mean value.

Electricity is dispatched according to the merit order – a ranking of energy sources according to their marginal costs – that gives the production function its "hockey-stick" shape. Flexible production with low start-up costs and the ability to adjust power generation quickly (most often based on gas, coal or oil) is responsible for setting the peak-time price. Inflexible production – nuclear and large thermal plants – set the price in off-peak hours. Hydropower is a rather flexible source of generation; its low marginal cost makes it well suited to provide electricity on baseload terms. The Nordic power market is a hydro-dominated system (around 60%), followed by nuclear (22%) and thermal generation. Wind generation is much smaller, delivering about 4% of the whole production at present but growing.

2.4.2. Urgent Market Messages dataset

According to market regulations, all members of Nord Pool must disclose information concerning changes to the conditions on the grid through UMMs. Information about failures, plans and changes of plans for maintenance or limitations affecting more than 100 MW of generation, consumption or transmission has to be reported publicly.[37] The messages can be broadly divided into two categories: information about failures and news about maintenance. News announcing failures has to be reported within 60 min. of an occurrence of an outage. There are no specific rules defining when the information about maintenance has to be made public. Market participants announce the messages though a special web-based portal; information is public and available in real-time to all interested parties through the Nord Pool webpage.[38]

The dataset is composed of messages issued by Nord Pool participants and contains 22,736 UMMs that were registered between the 1st of January 2006 and the 31st of December 2009. The dataset has a rich information structure. An individual message bears detailed information about the reported event, for example, the name of the company that is reporting news, type of news, affected capacity, time of the event start and an estimated end of the event. Each UMM has an individual registration time, which can be thought of as a point in time, but it also notifies about the start and estimated end of the event – a time interval. The estimated end of an event is often subject to change and follow-up messages inform of new estimates, as well as of the true end. In many cases the actual end of an event will be later that initially planned – the event will be prolonged – though sometimes it takes less time to restore the power system to normal than estimated and the event ends earlier.

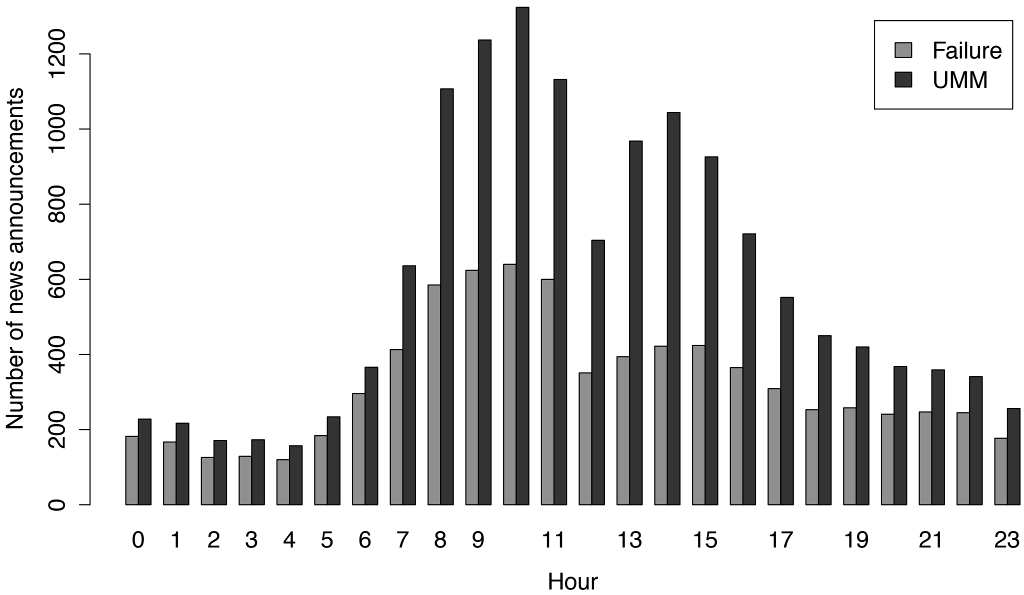
From the whole set I choose news that was not available while submitting the bidding strategies into the day-ahead market but arrived in time to influence decisions concerning the intra-day market. This leaves 14,091 messages whose content could possibly influence the price formation on the intra-day market. Among these, 7,752 correspond to failures, 4,999 to maintenance plans, 1,179 are "special information" and 161 inform about consumption or production changes. 12,153 UMMs were issued by market participants (producers and consumers) and 1,938 by the Transmission System Operators (TSOs). The arrival of messages is not distributed uniformly

[37] Implementation of annex to regulation EC 1228/2003 http://www.nordpoolspot.com/Documents/Exchange%20Information/EnclEIno78.pdf

[38] http://umm.nordpoolspot.com/messages/all

over the day. There are few messages in the early morning hours – between 00:00 and 05:59 – numbers grow over time with the peak around the time of the closure of the day-ahead market.

Figure 2. UMMs announcements by the time of the day



Note: This graph shows the total number of UMMs and UMMs informing about failures per hour.

Another important piece of information that I extract from the UMMs is the fuel type used by the market participant that reports the news. Failures of coal-based production units are most frequent – there are 2,557 messages informing about a failure of a coal plant in my dataset. Another important source of failures in the time frame that I study is hydro-generation with 2,429 UMMs and nuclear power plants with 824 messages. Moreover, as electricity is dispatched according to merit order, it is important to distinguish news informing about the marginal production from news about base-load generation. Therefore I group the UMMs into two categories: $Marg_t$ and $Base_t$.

Using the UMM dataset I create eight variables:
UMM$_t$ is the number of messages that arrived before hour t informing about a capacity change at hour t.
Failure$_t$ is the number of new messages that arrived before hour t informing about a failure at hour t.
NuclearFailure$_t$ is the number of new messages that arrived before hour t informing about a failure of nuclear production at hour t.
HydroFailure$_t$ is the number of new messages that arrived before hour t informing about a failure of hydro production at hour t.
CoalFailure$_t$ is the number of new messages that arrived before hour t informing about a failure of coal production at hour t.
Marg$_t$ is the number of new messages that arrived before hour t informing about problems reported by generation using coal, gas or oil at hour t.
Base$_t$ is the number of new messages that arrived before hour t informing about the problems reported by generation using nuclear or hydropower at hour t.
Additionally, I create the eighth variable *SizeOfOutage*$_t$, which measures the number of missing megawatts due to all failures announced in between the bidding for the two markets and happening at time t.

The *UMM*$_t$ variable is a "broader" variable than the *Failure*$_t$ one, as it contains not only information about failures, but also other information that became known after the closure of the day-ahead market and can impact the prices level on the intra-day market. It can also contain some maintenance information; in such a case it will be a follow-up message that brought some substantial, new piece of news like information about a change of the duration or of the size of the occurring maintenance.

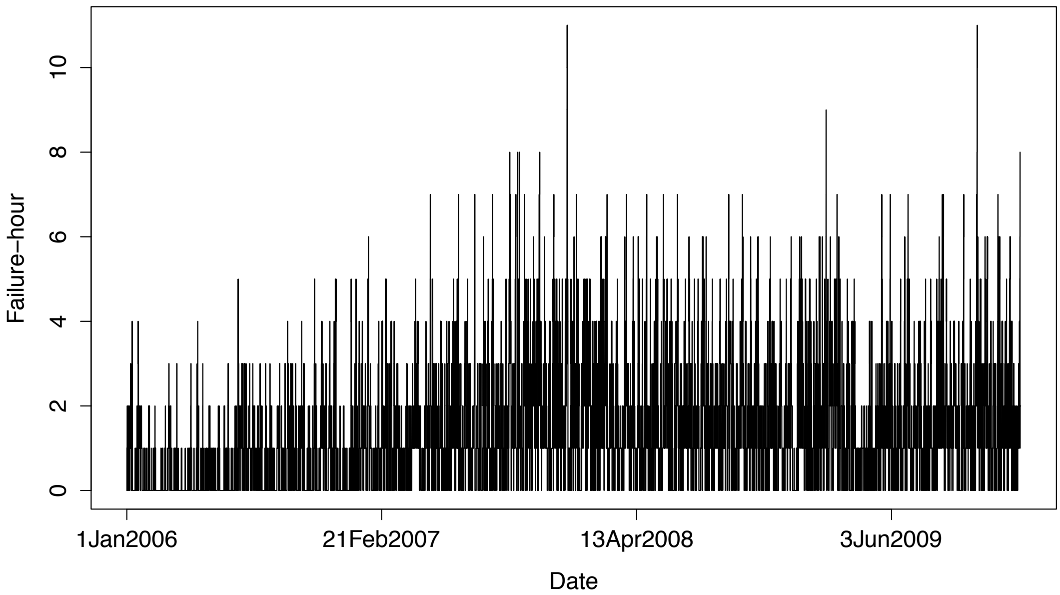
All these variables consider only information that arrived after the day-ahead market had already closed and while the intra-day was still open. These variables can also be interpreted as counts of failure-hours that became publicly known in between the biddings for the two markets, so after the closure of the day-ahead market. Therefore they can be thought of as representing events that affect supply and potentially prices on the intra-day market for a particular product delivered at time t, but have no effect on the price of this product at the day-ahead market.

It is interesting to note that the number of failure-hours per day that were registered in between the biddings for the two markets increased in 2006 and 2007 (Figure 3). The highest number of failure-hours per day was observed at the beginning of 2008, reaching the level of 179.

The failure-hour count sums all the hours of separate failures per day that could affect the prices on the intra-day market. Therefore, if there were two failures each of duration of five hours registered after the day-ahead market had closed and affecting the intra-day market, they would be counted as 10 failure-hours. The purpose of such a construction of the variables stems from the frequency of the data (hourly), the way the average intra-day price is calculated and the continuous nature of the intra-day market.

The intra-day market trades continuously; therefore, electricity that is delivered at a certain hour can be traded several times and at different prices. The average intra-day price that is used in this study is obtained from the Nord Pool FTP server and it is the average of all prices obtained for one product (there could be a difference of several hours between the times when this product was traded). A message that arrives at 15:00 and informs about a failure between 15:00 and 23:00 on the same day can affect trades for electricity that will be delivered between 16:00 and 23:00.

Figure 3. Count of failure-hours



Note: This figure shows the total of failure-hours registered every day between the 1st of Janury 2006 and the 31st of December 2009.

2.5. Empirical strategy

2.5.1. Premia

2.5.1.1. Definition

On the intra-day market, electricity can be traded up to one hour before delivery, while on the day-ahead market prices for each of the hours of the coming day are known around 13:00 on the day before the delivery. Both markets trade the same product but at different moments in time. As I am interested in price formation on the short-term electricity markets, I define the premium as the difference between the day-ahead price and the intra-day price.

$$Premium_t = "Day\_ahead\ price"_t - "Intra\_day\ price"_t = \beta + \varepsilon_t \quad (2)$$

2.5.1.2. Impact of information on premium

Information concerning the physical properties of the power grid (failures, maintenance, bottlenecks) plays a particular role. Physical characteristics on the grid can change quite rapidly, having an impact on the available size of the supply, and this is why it is important for market participants to have the most up-to-date information. In order to judge the relation of the price difference on these markets, market players need to update their information set Ω_t which at moment t includes price development (p) up to moment t-1 and last-minute information that reflects the most current information about market fundamental risk which, in this analysis, corresponds to the market news (UMM_t). These elements of the information set enable a market player to take a decision about the price at t for electricity.

$$\Omega_t = \{p_{t-1}, UMM_t\}$$

The presence of premia is influenced by the characteristics of the spot price,[39] but what seems even more important are events that occur in between the bidding for the two markets, in this case, after the day-ahead market has closed and before the closure of the intra-day market. Tomorrow's spot prices deviate from forward prices in the case of unexpected shocks that change the information set of bidders.

In the dataset of news, one type of information dominates – sudden capacity reductions due to unplanned outages – failures. Other categories of news, e.g., maintenance or special information, appear more sporadically. Increases in capacity appear as information about problems on the consumer side when, because of a halt in a consumer's production line, less electricity will be used. Other sources of capacity increase are due to follow-up news that informs about an event on the grid that provoked an initial capacity reduction but has ended earlier than estimated and thus the production unit is on-line earlier. For the period between the actual end of the event and the initially reported end, there is an increase of capacity due to the power unit being back in operation.

[39] Bessembinder and Lemmon (2002).

The relationship I estimate is described in Equation 3.

$$Premium_t = \beta_0 + \alpha_1 UMM_t + \gamma_1 Var_{t-1} + \gamma_2 Skew_{t-1} + \delta X_t + \varepsilon_{1t} \quad (3)$$

The UMM_t is the information at time t and Var_{t-1} and $Skew_{t-1}$ are price developments up to the last known moment t-1. Since the capacity reductions are the most frequent source of messages, the expected impact of the information on the premia is negative:

$$\frac{\partial Premium_t}{\partial\, UMM_t} < 0$$

As electricity prices are often autocorrelated, I account for the possible autocorrelation and estimate models with lagged variables structure – represented in Equation 3 by the vector X_t. The actual specifications I use (the number of the autoregressive and moving average lags) are obtained through a selection process of autocorrelation and partial autocorrelation charts as well as by the comparison of the Akaike Information Criteria (AIC). In the distributed lags models I often include ar6 and ar7 lags, which reflect weekly seasonality in the data. In the basic OLS specification, in order to capture weekly seasonality, I include day of the week dummies.

Electricity is dispatched according to the merit order and the most expensive production is used only in times of high demand – peak hours – while the base load production is constantly active. Due to this heterogeneity of production, it is interesting to verify the impact of messages informing about problems with different types of production.

In peak hours, most of available production is already in use and therefore the information about grid fundamentals should have the largest effect at these times. Prices are already high and a reduction in available capacity would mean that the missing production needs to be replaced by even more expensive production.

2.5.2. Analysis

I start the analysis by investigating the distribution of premia over 24 hours. I estimate Equation 4 separately for each hour. The coefficient on constant β informs about the size of the premium (Table 3, Column 1).

$$Premium_t = "Day\_ahead\ \mathrm{price}"_t - "Intra\_\mathrm{day}\ price"_t = \beta + \varepsilon_t \quad (4)$$

The day-ahead price is the Swedish price and the intra-day price is an average of the prices obtained for electricity for a particular hour. It covers all trades for the particular product.[40] It does not include any time constraints for when the trade took place as long as the traded product was the same. Further on, I evaluate the impact of the last-minute market-specific information (UMM) on the premium (Equation 5). The impact of information about failures is estimated in Equation 6.

$$Premium_t = \beta_0 + \alpha_1 UMM_t + \gamma_1 Var_{t-1} + \gamma_2 Skew_{t-1} + \delta X_t + \varepsilon_{1t} \quad (5)$$

$$Premium_t = \beta_1 + \alpha_2 Failure_t + \gamma_3 Var_{t-1} + \gamma_4 Skew_{t-1} + \delta_2 X + \varepsilon_{2t} \quad (6)$$

It is not only the appearance of the information per se, but also the content of the information that has an effect on premia. It is important which market fundamentals are changed. Among those that are expected to influence the premia are the ones impacting generation mix – fuels.[41] Therefore Equation 8 distinguishes the events from Equation 5 into those that affect marginal production (*Marg*) or base-load production (*Base*). Equation 7

[40] The intra-day market functions as a continuous discriminatory auction as opposed to the day-ahead market, which is a uniform auction.

[41] Some studies have shown that fuel costs may not influence high-frequency electricity prices (Guirguis and Felder 2004), one of the reasons being their slow evolution over the studied period (Karakatsani and Bunn 2008). In this study I do not attempt to use fuel prices per se; rather, I am interested what effects sudden changes in production using a particular fuel have on premia.

again examines failures, but tests separately for the impact of the three fuels that report failures most often – coal, nuclear and hydro.

$$Premium_t = \beta_2 + \alpha_3 Coal\ Failure_t + \alpha_4 Nuclear\ Failure_t + \alpha_5 Hydro\ Failure_t + \gamma_5 Var_{t-1} + \gamma_6 Skew_{t-1} + \delta_3 X + \varepsilon_{4t} \quad (7)$$

$$Premium_t = \beta_3 + \alpha_6 Marg_t + \alpha_7 Base_t + \gamma_7 Var_{t-1} + \gamma_8 Skew_{t-1} + \delta_4 X_t + \varepsilon_{3t} \quad (8)$$

All equations take into account the effect of the variance and the skewness of the underlying spot price on premia. In order to take into account weekly seasonality, I include a vector of dummies (in the OLS specification) X_t representing the days of the week (from Monday to Saturday). The variables *UMM*, *Failure*, *Marg*, *Base*, *Coal Failure*, *Nuclear Failure* and *Hydro Failure* measure the number of messages that arrive before hour t and inform about capacity changes due to different reasons at hour t. This information is novel and unscheduled; therefore, variables are exogenous.[42]

Market participants are assumed to derive information about the day-ahead distribution of electricity prices by observing the moments of the underlying intra-day price distribution up to the last available moment t-1; therefore, each specification includes rolling-window variance and skewness of the intra-day price calculated on the basis of the last 24 hours.

Not only the intensity of failures, measured as the count of separate messages informing about failures, might have an effect on premia, but also size of an outage itself potentially plays a role. A single large outage will potentially have a greater impact than many small ones, as more capacity needs to be replaced from more expensive sources of generation. I account for this effect and verify the effect of the severity of an outage (number of missing MW) on premium in Equation 9.

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[42] In this analysis I examine only messages that come in between the biddings for the two markets when potential problems with strategic scheduling of outages do not seem very likely. Strategic timing of messages could influence the results only if it occurred with the intention of impacting the intra-day price.

$$Premium_t = \beta_4 + \alpha_8 SizeOfOutage_t + \gamma_8 Var_{t-1} + \gamma_9 Skew_{t-1} + \delta_5 X + \varepsilon_{4t} \quad (9)$$

Each equation (5 – 9) is tested separately for every hour giving in total 24 models for each specification. I estimate these models using OLS with Newey-West standard errors (HAC) to address correlation and heteroscedasticity of the error terms.

To test for autocorrelation, I estimate models with the lagged variables specifications. The final choice of a specific ARMA model has been made with the use of AIC and BIC criteria as well as autocorrelation and partial correlation plots.

2.6. Results

2.6.1. Premia

Results indicate (Table 3, Column 2) that premia between the intra-day and the day-ahead prices exist and that their sign varies throughout the day. Apart from hours 16 and 23, all premia are statistically significantly different from zero.

Table 3. Existence of premia and market-specific news and its impact on premia

Premia	*Const.*	*UMM*	*Marginal*	*Base*	*Missing MW*
Premium h0	0.891	-0.211	0.020	-0.360	-0.067
	(0.117)***	(0.091)*	(0.200)	(0.131)**	(0.040)
Premium h1	1.360	-0.107	0.067	-0.244	-0.057
	(0.124)***	(0.090)	(0.190)	(0.130)	(0.040)
Premium h2	1.594	-0.094	0.225	-0.344	-0.058
	(0.141)***	(0.108)	(0.250)	(0.145)*	(0.045)
Premium h3	1.761	-0.029	0.107	-0.136	-0.070
	(0.141)***	(0.092)	(0.176)	(0.149)	(0.039)
Premium h4	1.531	-0.076	0.075	-0.200	-0.068
	(0.134)***	(0.096)	(0.167)	(0.152)	(0.037)

Premium h5	0.592	0.276	0.475	-0.001	0.001
	(0.259)**	(0.216)	(0.261)	(0.227)	(0.063)
Premium h6	-0.530	-0.073	0.046	-0.047	-0.079
	(0.226)**	(0.224)	(0.266)	(0.213)	(0.056)
Premium h7	-2.653	-0.641	-1.317	-0.043	-0.176
	(0.308)***	(0.266)*	(0.412)**	(0.299)	(0.072)*
Premium h8	-3.122	-0.867	-1.611	-0.264	-0.278
	(0.295)***	(0.259)***	(0.407)***	(0.295)	(0.073)***
Premium h9	-3.460	-1.014	-1.420	-0.778	-0.344
	(0.291)***	(0.235)***	(0.404)***	(0.297)**	(0.068)***
Premium h10	-3.847	-1.136	-1.312	-1.029	-0.384
	(0.323)***	(0.247)***	(0.374)***	(0.299)***	(0.081)***
Premium h11	-4.612	-0.945	-1.047	-0.876	-0.264
	(0.360)***	(0.249)***	(0.383)**	(0.311)**	(0.089)***
Premium h12	-3.230	-0.741	-0.763	-0.752	-0.244
	(0.246)***	(0.162)***	(0.234)**	(0.239)**	(0.061)***
Premium h13	-2.545	-0.473	-0.751	-0.433	-0.227
	(0.228)***	(0.142)***	(0.228)***	(0.211)*	(0.051)***
Premium h14	-1.952	-0.331	-0.447	-0.268	-0.155
	(0.212)***	(0.115)**	(0.181)*	(0.170)	(0.042)***
Premium h15	-1.515	-0.183	-0.404	-0.148	-0.111
	(0.233)***	(0.168)	(0.245)	(0.185)	(0.054)*
Premium h16	-1.014	-0.831	-1.552	-0.640	-0.232
	(0.787)	(0.688)	(1.062)	(0.566)	(0.161)
Premium h17	-2.844	-1.139	-2.487	-0.979	-0.411
	(0.914)**	(0.668)	(1.246)*	(0.610)	(0.201)*
Premium h18	-3.791	-0.560	-0.762	-0.428	-0.206
	(0.372)***	(0.171)**	(0.303)*	(0.267)	(0.066)**
Premium h19	-2.321	-0.611	-0.914	-0.352	-0.189
	(0.212)***	(0.119)***	(0.209)***	(0.158)*	(0.043)***
Premium h20	-1.361	-0.464	-0.710	-0.387	-0.182
	(0.153)***	(0.072)***	(0.145)***	(0.120)**	(0.032)***
Premium h21	-0.935	-0.126	-0.268	-0.043	-0.095
	(0.147)***	(0.085)	(0.133)*	(0.108)	(0.034)***
Premium h22	-0.790	-0.299	-0.417	-0.216	-0.131
	(0.119)***	(0.058)***	(0.099)***	(0.096)*	(0.024)***
Premium h23	0.040	-0.089	-0.142	-0.078	-0.067
	(0.099)	(0.05)	(0.076)	(0.075)	(0.020)***

Note: This table presents results from regressions of which details are provided below. Column 2 reports the evolution of the average difference between the day-ahead and the intra-day price - the premium over a day. Column 3 reports coefficient α_1 from the equation

$Premium_t = \beta_0 + \alpha_1 UMM_t + \gamma_1 Var_{t-1} + \gamma_2 Skew_{t-1} + \delta X_t + \varepsilon_{1t}$ Columns 4 and 5 report coefficients α_6 and α_7 from equation

$Premium_t = \beta_3 + \alpha_6 Marg_t + \alpha_7 Base_t + \gamma_7 Var_{t-1} + \gamma_8 Skew_{t-1} + \delta_4 X_t + \varepsilon_{3t}$

In all regressions OLS with Newey-West standard errors procedure is used separately for each hour. The R-squares for different equations are in range from 0.01 to 0.278 for results in Column 3 and from 0.01 to 0.28 for specification in Columns 4 and 5.

Column 6 reports coefficient α_8 from equation

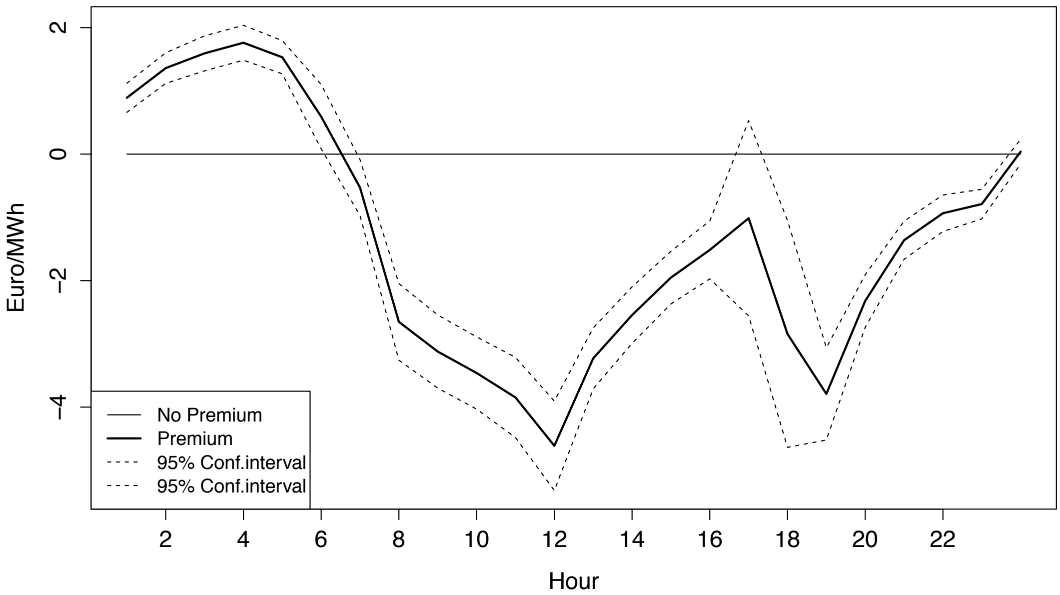
$Premium_t = \beta_4 + \alpha_8 SizeOfOutage_t + \gamma_8 Var_{t-1} + \gamma_9 Skew_{t-1} + \delta_5 X + \varepsilon_{4t}$

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Figure 4, which plots constant values from Equation 2 for each of the 24 regressions, shows the premia and displays a clear pattern of positive premia in the off-peak hours and negative premia in the peak hours. Negative premia prevail, indicating that for most of the time the intra-day price is higher than the day-ahead one, making it more expensive for market participants to balance their position by buying the electricity closer to the real time. At its peak, hour 11, it is 4.6€ higher than the price of electricity sold with the day-ahead contract, which represents a 9.2% (negative) premium. Positive premia occur in the early morning hours with the peak around 3 o'clock – a 5.43%[43] premium. Evolution of premia over time for chosen hours is presented in the Appendix: Figures 5, 6 and 7.

[43] Compared with the intra-day mean price for the hour.

Figure 4. Average premium over a day



Note: This figure shows the evolution of an average forward premium (calculated as the difference between the day-ahead and the intra-day price on the Nord Pool, 2006 – 2009) over 24 hours.

2.6.2. Impact of information about failures on premia

UMMs have an impact on premia mostly in the peak hours (Table 3, Column 3). The largest impact is identified in the morning, when the arrival of messages decreases the premium by 1.1€, which constitutes almost 30% of the mean premium observed for that hour (hour 10 with a 3.847 negative premium). As the UMM dataset contains different news categories, I divide the UMMs according to different fuel types. Further on I distinguish news concerning outages from the other types of news and report the results for the three most frequent failures. Messages informing about changes to production or consumption affecting marginal types of units are significant for 14 out of 24 hours (Table 3, Column 4) and news informing about changes to base-load for 10 out of 24 hours (Table 3, Column 5). The negative effect on premia of news concerning changes in marginal production is observed mainly during peak-hours, while news concerning changes in base-load production has a negative impact on premia even in off-peak hours. The effect of marginal production's news reaches the highest level at hour 17 (Table 3, Column 4), which constitutes 87% of the mean premium observed for this time of the day (hour 17 with 2.844 negative premium; Table 3, Column 2).

As can be expected, failures have a negative effect on premia. Breakdowns on the production site or transmission grid lead to less available electricity and thus prices on the intra-day market rise (Table 4). Failure coefficients are significant for 17 out of 24 hours; new information about a failure raises the intra-day price with the increase ranging from 0.2€ to 1.3€, having an overall negative effect on the premium.

Table 4. Impact of messages informing about failures on premia

Premia	*Failure*	*Failure coal*	*Failure nuclear*	*Failure hydro*
Premium h0	-0.269	-0.000	-0.830	-0.233
	(0.106)*	(0.230)	(0.329)*	(0.162)
Premium h1	-0.209	-0.106	-0.665	-0.235
	(0.104)*	(0.192)	(0.379)	(0.155)
Premium h2	-0.190	0.090	-0.877	-0.265
	(0.139)	(0.412)	(0.386)*	(0.188)
Premium h3	-0.090	-0.175	-1.193	0.057
	(0.110)	(0.230)	(0.372)**	(0.180)
Premium h4	-0.108	-0.210	-1.379	0.069
	(0.113)	(0.207)	(0.396)***	(0.168)
Premium h5	0.187	0.059	-0.608	0.120
	(0.218)	(0.300)	(0.436)	(0.222)
Premium h6	-0.197	-0.521	-0.045	-0.127
	(0.198)	(0.265)*	(0.465)	(0.205)
Premium h7	-0.591	-1.445	0.634	-0.194
	(0.264)*	(0.449)**	(0.612)	(0.357)
Premium h8	-0.792	-1.535	-1.073	-0.349
	(0.243)**	(0.484)**	(0.733)	(0.340)
Premium h9	-1.065	-1.328	-0.566	-1.173

	(0.219)***	(0.504)**	(0.689)	(0.425)**
Premium h10	-1.133	-1.401	-1.089	-1.281
	(0.222)***	(0.453)**	(0.750)	(0.379)***
Premium h11	-0.831	-1.084	-0.112	-0.948
	(0.245)***	(0.461)*	(0.739)	(0.423)*
Premium h12	-0.837	-0.910	-0.091	-1.017
	(0.195)***	(0.326)**	(0.500)	(0.312)**
Premium h13	-0.607	-1.141	-0.264	-0.451
	(0.173)***	(0.324)***	(0.470)	(0.300)
Premium h14	-0.383	-0.528	-0.815	-0.211
	(0.142)**	(0.238)*	(0.412)*	(0.246)
Premium h15	-0.254	-0.465	-0.822	0.044
	(0.153)	(0.304)	(0.486)	(0.197)
Premium h16	-0.722	-1.244	-1.015	-0.051
	(0.553)	(1.002)	(0.941)	(0.531)
Premium h17	-1.308	-2.622	0.022	-0.684
	(0.664)*	(1.344)	(1.295)	(0.662)
Premium h18	-0.688	-0.973	0.410	-0.777
	(0.206)***	(0.425)*	(0.509)	(0.344)*
Premium h19	-0.582	-0.968	0.207	-0.473
	(0.138)***	(0.279)***	(0.361)	(0.220)*
Premium h20	-0.538	-1.042	-0.161	-0.389
	(0.100)***	(0.216)***	(0.270)	(0.171)*
Premium h21	-0.194	-0.424	-0.163	-0.080
	(0.098)*	(0.177)*	(0.265)	(0.142)
Premium h22	-0.343	-0.699	-0.553	-0.166
	(0.080)***	(0.172)***	(0.232)*	(0.123)
Premium h23	-0.132	-0.250	-0.433	-0.063
	(0.064)*	(0.107)*	(0.211)*	(0.104)

Note: This table presents results from regressions which details are provided below.

Column 2 shows coefficient α_2 from equation

$Premium_t = \beta_1 + \alpha_2 Failure_t + \gamma_3 Var_{t-1} + \gamma_4 Skew_{t-1} + \delta_2 X + \varepsilon_{2t}$

Columns 3, 4 and 5 show coefficients α_3, α_4 and α_5 from equation

$Premium_t = \beta_2 + \alpha_3 Coal\ Failure_t + \alpha_4 Nuclear\ Failure_t + \alpha_5 Hydro\ Failure_t + \gamma_5 Var_{t-1} + \gamma_6 Skew_{t-1} + \delta_3 X + \varepsilon_{4t}$

In all regressions, OLS with Newey-West standard errors procedure is used separately for each hour. The R-squares for different equations range from 0.01 to 0.027 for both specifications.

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

The results from distributed lag models deliver similar results and are presented for chosen hours in the Appendix (Tables A1 – A4). Adding extra autoregressive terms improves the fit of the model and decreases the level of AIC criterion. The autoregressive terms with six and seven lags (ar6 and ar7) are often significant, indicating the weekly seasonality.

The results presented so far indicate that messages about sudden events on the grid significantly impact the price difference between the day-ahead and the intra-day electricity markets. It is, however, of interest to verify the impact of the news as compared to the impact of other factors that explain the premium. In the Appendix (Tables A5 – A9) I present standardized coefficients from Equations 5 – 9. The results indicate that a one standard deviation increase in *UMM* leads to a decrease of at most 0.18 standard deviations in the premium, with the other variables held constant. The results for the marginal fuels variable, *Marg*, look similar. A one standard deviation increase in *Marg* leads to a decrease in the premium that is between 0.06 and 0.14 of a standard deviation. A similar effect for premium (between 0.06 and 0.1) is observed for a one standard deviation increase in the *Base* variable, which counts the number of messages informing about changes to nuclear or hydro production.

2.6.3. Information about the failure of particular generation types and their impact on premia

During the period that I analyse, the hydro-based generation has registered breakdowns for the longest time-periods. Outages observed by the hydro production amounted to 17,797 hours in total. Coal plant failures were reported to last 14,712 hours in total and the nuclear generation's failures covered 4,040 hours.

Breakdowns of units based on coal have the largest effect on the premia – coal failure coefficients are significant for 16 out of 24 hours. The price difference caused by this type of breakdown can reach up to 2.6€ per MWh, which constitutes 92% of the mean premium observed for this hour (hour 17 with 2.844 negative premium; Table 3, Column 2). Coal-based production is often used during peak hours when the demand is high and therefore prices are subsequently high too. A malfunction during this time period leads to a scarcity of marginal production. In order to sustain the supply and balance it with demand, other units, possibly more expensive, have to start their production (or increase their production which, due to ramping costs, is more expensive).

In all specifications I observe weekly seasonality, with working days having a significant negative U-shaped effect on premia in the peak-hours. The results from ARMA models are in line with the above results and the inclusion of autoregressive terms, although it improves the fit (indicated by the autocorrelation plots and AIC criteria), does not change the estimated coefficients on the failures variables substantially.[44]

The results in Table 4 show that a one standard deviation increase in coal failures decreases premiums by, at most, 0.16 of a standard deviation. A one standard deviation increase in nuclear failure leads to a 0.08 standard deviation decrease in premium and a one standard deviation increase in hydro failure lowers the premium by 0.1 of a standard deviation. A one standard deviation increase in the skewness and variance of the intra-day price leads to a larger impact on the premium than failure variables. However, variables measuring the impact of news are more often significant.

As a part of a sensitivity analysis, I run the same regressions as in Equations 5 through 8, but using dummy variables for "news" and "no news" hours instead of the total number of messages per hour. The obtained results (Tables A10 and A11) are similar to the original ones, with the absolute effects slightly larger in the dummy variable specifications.

2.6.4. Missing capacity and its impact on premia

The impact of the size of an outage on the price difference between the day-ahead and the intra-day electricity price is significant for 16 out of 24 hours (Table 3, Column 6). The largest effect is observed for hour 17, when 100 MW of missing capacity decreases the premium by 0.4€. Seeing that the mean size of the outage at that time is 424 MW, the premium can decrease by 1.6€. A one standard deviation increase in the size of the outage leads to a 0.16 standard deviation decrease in premium (Table A9).

[44] A comparison of results from OLS and ARMA specifications for chosen hours is presented in Tables A1-A4.

2.7. Conclusions

This paper studies the impact of market-specific news on the short-term forward premia on the Nordic electricity market – Nord Pool. The contribution of the paper is three-fold. First, I indicate that last-minute market-specific news is important for the explanation of the premia on the electricity market. I show that the short-term forward premia are in general negative with a clear pattern emerging during the day – positive premia during off-peak hours and negative premia during peak hours. I associate the emergence of this pattern with the arrival of news that becomes known in the time slot between the bidding for the two markets. In the news dataset one type of information – capacity reductions – prevails, which lowers the premium. All information announced by UMMs is relevant to the market, making the dataset ideal to study the impact of news on price behaviour.

Second, using as an example the intra-day and the day-ahead electricity markets, I study the nature of short-time premia on the Nord Pool. Due to increased amounts of intermittent renewable power that are being brought on-line, the intra-day electricity markets are expected to become more important over time and carry more trade as they give an opportunity to trade power closer to real time. Unlike the day-ahead market, futures markets and the real-time (balancing) market that have gained much attention in the literature, the intra-day market has not been subject to a deeper analysis. Forward premia of different horizons have been studied in a variety of markets, but the intra-day market has been largely left out of the analysis. Since this market is growing, it is important to understand the price difference between this and the "main" day-ahead market.

The third contribution is to verify how messages, informing about sudden events affecting the power market, influence the premia. I show that information about the supply-side shocks affecting different fuel types have a significant impact on the price differences between the two markets and should be taken into account while discussing short-term premia. During the analysed period, failures in coal-based generation had the biggest impact on the premia.

The paper shows that although the sign of the premia fluctuates over time in short time markets, it is mostly negative, indicating that in peak hours the intra-day price is higher than the day-ahead price. This finding is in opposition to the studies that describe premia of longer horizon where it is the future price that is higher than the spot price.[45] The high intra-day price can be seen as a reimbursement for sellers who keep extra capacity close to the real-time and therefore bear the risk of not selling if there is no demand – thus it reflects the market fundamentals risk.

The results indicate that information concerning shocks to the power system should be included in the analysis of premia, as it explains part of the difference between the day-ahead and the intra-day prices. On the Nord Pool's day-ahead and intra-day markets, market-specific news is responsible for the occurrence of premia. However, it cannot explain all price differences, indicating that premia on this market do exist even after accounting for shocks.

[45] Redl et al. (2009) find positive premia for one-month ahead premia; and Botterud et al. (2010) find positive premia for several weeks ahead; both studies describe the Nordic electricity market.

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Appendix

Figure 5. Premium for hour 7 over time

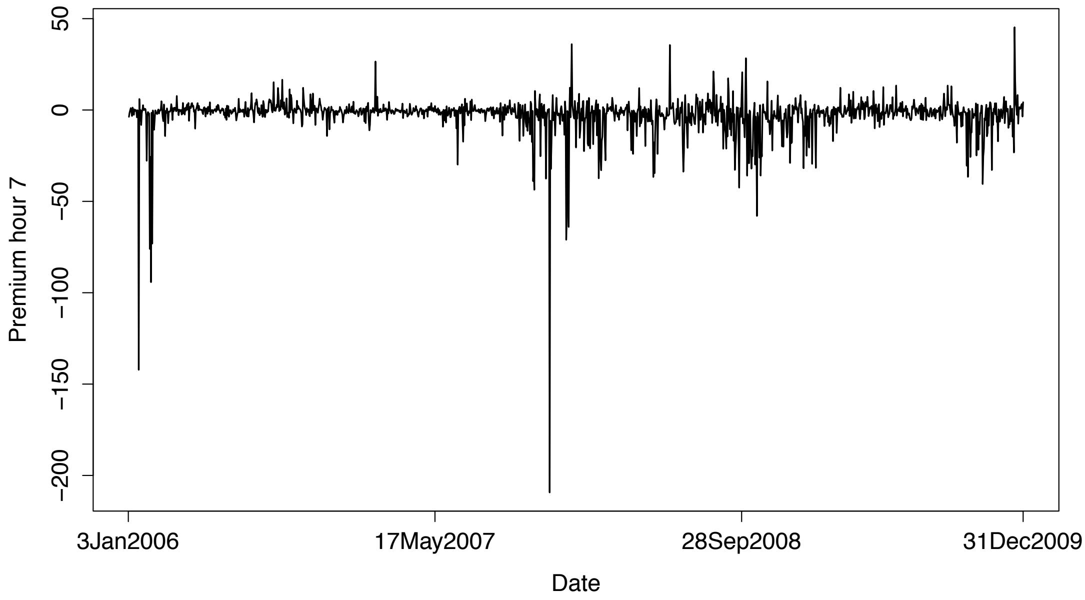


Figure 6. Premium for hour 18 over time

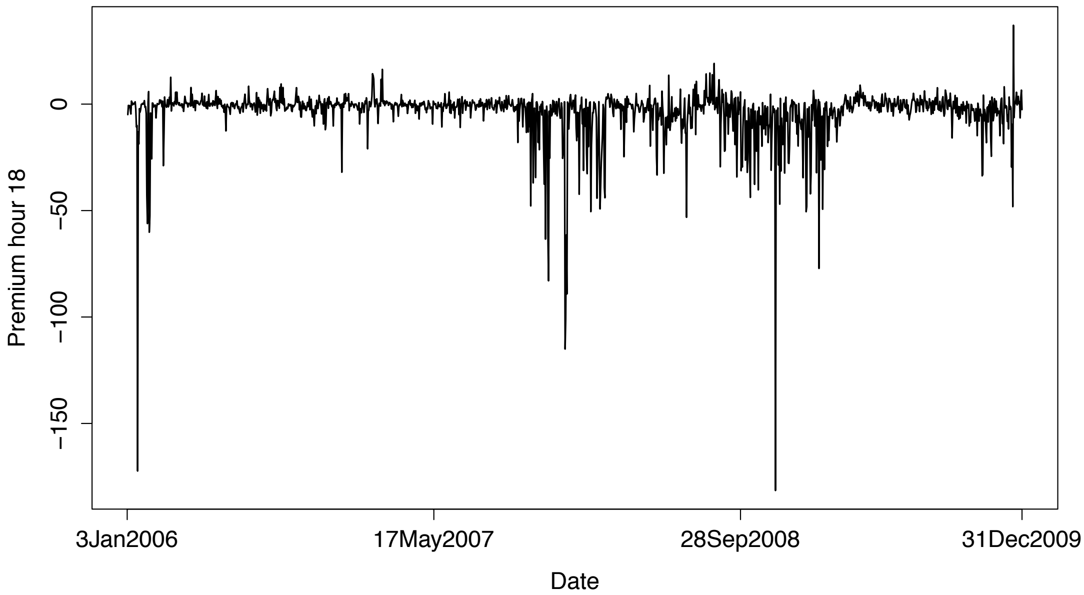


Figure 7. Premium for hour 22 over time

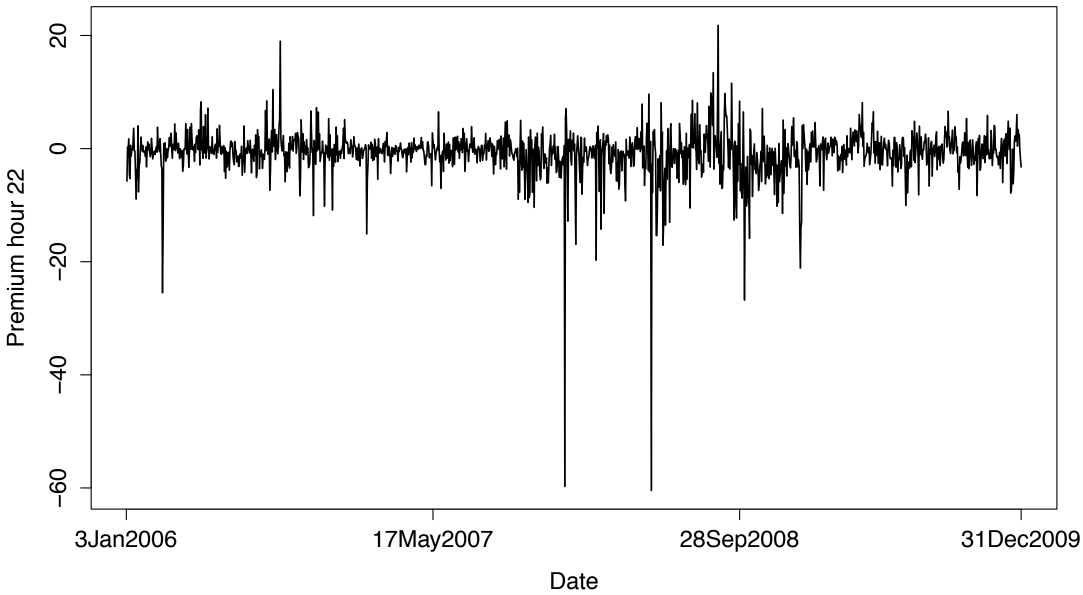


Table A1. Market-specific news and its impact on premia for chosen hours

	Hour 7		Hour 18		Hour 22	
UMM	-0.641	-0.574	-0.56	-0.326	-0.299	-0.282
	(0.266)*	(0.219)**	(0.17)**	(0.182)*	(0.06)***	(0.058)***
Skewness	-4.67e-06	-9.4e-06	0.00002	0.00001	0.00001	0.00002
	(0.000025)	(4.4e-06) *	(0.00003)	(2.9e-06)***	(0.00001)	(1.2e-06)***
Variance	-0.0015	0.0005	-0.01	-0.008	-0.0023	-0.002
	(0.0033)	(0.0007)	(0.009)	(0.0003)***	(0.0014)	(0.0002) ***
ar1	-	0.097	-	0.14	-	0.95
	-	(0.02)***	-	(0.01)***	-	(0.02) ***
ar2	-	0.120	-	0.07	-	-
	-	(0.014)***	-	(0.02)***	-	-
ar3	-	0.04	-	0.06	-	-
	-	(0.03)	-	(0.02)***	-	-
ar4	-	0.016	-	0.07	-	-
	-	(0.02)	-	(0.02)***	-	-
ar5	-	-0.042	-	0.04	-	-
	-	(0.027)	-	(0.02)	-	-
ar6	-	0.11	-	0.07	-	-
	-	(0.018)***	-	(0.02) ***	-	-
ar7	-	0.0883077	-	0.13	-	-
	-	(0.02) ***	-	(0.02) ***	-	-
ma1	-	-	-	-	-	-0.9
	-	-	-	-	-	(0.03) ***

Note: This table presents a comparison of estimation results for chosen hours from Equation 5 estimated with OLS methods with Newey-West standard errors and ARMAX specifications.

$Premium_t = \beta_0 + \alpha_1 UMM_t + \gamma_1 Var_{t-1} + \gamma_2 Skew_{t-1} + \delta X_t + \varepsilon_{1t}$

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table A2. Market-specific news and its impact on premia for chosen hours

Variable	Hour 7		Hour 18		Hour 22	
Marginal	-1.317	-1.08	-0.762	-0.457	-0.42	-0.37
	(0.4) **	(0.4)**	(0.3) *	(0.324)	(0.09) ***	(0.099) ***
Baseload	-0.043	0.0007	-0.428	-0.323	-0.022	-0.25
	(0.3)	(0.479)	(0.267)	(0.269)	(0.096) *	(0.09)**
Skewness	-4.65e-06	-0.00001	0.00002	0.00001	0.00002	0.00002
	(0.00002)	(4.43e-06)**	(0.00003)	(2.89e-06)***	(0.00001)	(1.2e-06)***
Variance	-0.002	0.0005	-0.01	-0.008	-0.002	-0.002
	(0.003)	(0.0007)	(0.009)	(0.0003)***	(0.0014)	(0.0002)***
ar1	-	0.095	-	0.14	-	0.95
	-	(0.017) ***	-	(0.013)***	-	(0.02)***
ar2	-	0.123	-	0.071	-	-
	-	(0.014) ***	-	(0.02)***	-	-
ar3	-	0.0424	-	0.056	-	-
	-	(0.026)	-	(0.02)**	-	-
ar4	-	0.013	-	0.072	-	-
	-	(0.0198)	-	(0.018)***	-	-
ar5	-	-0.0415	-	0.036	-	-
	-	(0.027)	-	(0.022)	-	-
ar6	-	0.109	-	0.07	-	-
	-	(0.018) ***	-	(0.022)***	-	-
ar7	-	0.094	-	0.13	-	-
	-	(0.019) ***	-	(0.02)***	-	-
ma1	-	-	-	-	-	-0.897
	-	-	-	-	-	(0.027)***

Note: This table presents a comparison of estimation results for chosen hours from Equation 8 estimated with OLS methods with Newey-West standard errors and ARMAX specifications.

$$Premium_t = \beta_3 + \alpha_6 Marg_t + \alpha_7 Base_t + \gamma_7 Var_{t-1} + \gamma_8 Skew_{t-1} + \delta_4 X_t + \varepsilon_{3t}$$

p < 0.05; ** p < 0.01; *** p < 0.001

Table A3. Market-specific news and its impact on premia for chosen hours

Variable	*Hour 7*		*Hour 18*		*Hour 22*	
Failure	-0.6	-0.5	-0.69	-0.39	-0.34	-0.32
	(0.264) *	(0.33)	(0.21)***	(0.2)	(0.08)***	(0.06) ***
Skewness	-5.56e-06	-0.00001	0.00002	0.000014	0.00001	0.00002
	(0)	(4.4e-06)*	(0.00003)	(2.85e-06)***	(0)	(1.24e-06) ***
Variance	-0.002	0.0005	-0.01	-0.008	-0.002	-0.002
	(0.0033)	(0.0007)	(0.009)	(0.0003)***	(0.0014)	(0.0002)***
ar1	-	0.1	-	0.14	-	0.95
	-	(0.02)***	-	(0.01)***	-	(0.021)***
ar2	-	0.12	-	0.07	-	-
	-	(0.015)***	-	(0.02)***	-	-
ar3	-	0.04	-	0.05	-	-
	-	(0.03)	-	(0.02)**	-	-
ar4	-	0.02	-	0.07	-	-
	-	(0.02)	-	(0.02)***	-	-
ar5	-	-0.04	-	0.04	-	-
	-	(0.03)	-	(0.02)	-	-
ar6	-	0.11	-	0.07	-	-
	-	(0.02)***	-	(0.02)***	-	-
ar7	-	0.09	-	0.13	-	-
	-	(0.02)***	-	(0.02)***	-	-
ma1	-	-	-	-	-	-0.89
	-	-	-	-	-	(0.029) ***

Note: This table presents a comparison of estimation results for chosen hours from Equation 6 estimated with OLS methods with Newey-West standard errors and ARMAX specifications.

$Premium_t = \beta_1 + \alpha_2 Failure_t + \gamma_3 Var_{t-1} + \gamma_4 Skew_{t-1} + \delta_2 X + \varepsilon_{2t}$

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table A4. Market-specific news and its impact on premia for chosen hours

Variable	*Hour 7*		*Hour 18*		*Hour 22*	
Coal	-1.45	-1.33	-0.973	-0.441	-0.699	-0.665
failure	(0.45)**	(0.53) *	0.425 *	(0.419)	(0.17) ***	(0.114)***
Nuclear	0.63	0.58	0.41	0.09	-0.553	-0.6
failure	(0.61)	(1.57)	0.5	(1.05)	(0.232)*	(0.3)*
Hydro	-0.19	-0.07	-0.78	-0.55	-0.17	-0.017
failure	(0.36)	(0.57)	0.34*	(0.35)	(0.12)	(0.116)
Skewness	-6.08e-06	-0.00001	0.00002	0.00002	0.00002	0.000015
	(0.00002)	(4.46e-06) *	0.00003	(2.99e-06) ***	(0.00001)	(1.27e-06) ***
Variance	-0.002	0.0006	-0.01	-0.008	-0.002	-0.0023
	(0.003)	(0.0007)	0.009	(0.0003) ***	(0.0014)	(0.0001)***
ar1	-	0.1	-	0.14	-	0.6
	-	(0 .017)***	-	(0.014)***	-	(0.08)***
ar2	-	0.12	-	0.07	-	-
	-	(0.014)***	-	(0.02)***	-	-
ar3	-	0.04	-	0.05	-	-
	-	(0.03)	-	(0.02)**	-	-
ar4	-	0.02	-	0.07	-	-
	-	(0.02)	-	(0.02)***	-	-
ar5	-	-0.04	-	0.03	-	-
	-	(0.03)	-	(0.02)	-	-
ar6	-	0.11	-	0.07	-	-
	-	(0.018)***	-	(0.02)**	-	-
ar7	-	0.09	-	0.13	-	-
	-	(0.02) ***	-	(0.02)***	-	-
ar20	-	-	-	0.1	-	-
	-	-	-	(0.2)***	-	-
ar11	-	-	-	-	-	0.09
	-	-	-	-	-	(0.02)***
ar16	-	-	-	-	-	-0.035
	-	-	-	-	-	(0.02)
ma1	-	-	-	-	-	-0.489
	-	-	-	-	-	(0.09)***

Note: This table presents a comparison of estimation results for chosen hours from Equation 7 estimated with OLS methods with Newey-West standard errors and ARMAX specifications.

$Premium_t = \beta_2 + \alpha_3 Coal\ Failure_t + \alpha_4 Nuclear\ Failure_t + \alpha_5 Hydro\ Failure_t + \gamma_5 Var_{t-1} + \gamma_6 Skew_{t-1} + \delta_3 X + \varepsilon_{4t}$

p < 0.05; ** p < 0.01; *** p < 0.001

Table A5. Impact of messages informing about failures on premia

	UMM	*Sk.*	*Var.*	*Mon*	*Tue*	*Wed*	*Fri*	*Sat*	*Sun*
premium0	**-0.06**	-0.04	0.01	**0.06**	0.04	**0.08**	0.04	0.02	**0.08**
premium1	-0.03	**0.08**	0.00	**0.08**	**0.07**	0.06	0.06	0.05	**0.08**
premium2	-0.02	-0.04	0.04	0.04	0.01	0.05	0.05	0.01	0.08
premium3	-0.01	-0.09	0.09	0.08	0.01	0.05	0.06	-0.01	0.03
premium4	-0.02	-0.06	0.05	0.09	0.03	0.06	0.03	-0.01	0.04
premium5	0.04	0.07	-0.17	0.08	0.06	0.05	0.01	0.06	0.08
premium6	-0.01	-0.03	-0.15	0.05	0.03	0.02	0.00	0.13	0.15
premium7	**-0.08**	-0.02	-0.05	-0.01	-0.04	-0.04	0.00	**0.11**	**0.12**
premium8	**-0.12**	-0.18	0.06	-0.04	-0.06	-0.04	-0.02	**0.09**	**0.11**
premium9	**-0.15**	0.16	-0.20	-0.06	-0.06	-0.06	-0.04	**0.06**	**0.08**
premium10	**-0.16**	0.35	**-0.39**	-0.07	0.00	-0.02	-0.04	**0.07**	**0.10**
premium11	**-0.13**	0.41	-**0.53**	-0.02	-0.02	0.01	-0.02	**0.08**	**0.11**
premium12	**-0.15**	**0.49**	**-0.56**	-0.02	-0.01	0.04	-0.02	0.05	**0.12**
premium13	**-0.11**	**0.50**	**-0.61**	-0.04	-0.06	-0.03	-0.03	0.03	**0.09**
premium14	**-0.09**	**0.48**	**-0.57**	-0.06	-0.04	0.01	0.00	**0.07**	**0.09**
premium15	-0.05	0.66	-0.73	0.00	-0.01	0.05	-0.03	0.05	0.08
premium16	-0.06	-0.01	0.48	-0.05	-0.06	-0.04	-0.08	-0.01	0.01
premium17	-0.07	-0.03	0.56	-0.03	-0.04	-0.02	-0.04	0.03	0.04
premium18	**-0.09**	0.07	-0.33	**-0.09**	-0.06	-0.02	0.03	0.01	**0.05**
premium19	**-0.17**	0.18	-0.13	-0.03	-0.03	-0.02	0.01	0.05	0.04
premium20	**-0.18**	0.16	-0.09	-0.06	-0.03	-0.01	-0.01	0.04	0.02
premium21	-0.05	0.22	-0.33	0.01	0.00	0.03	-0.02	0.08	0.07
premium22	**-0.15**	0.18	-0.22	-0.02	-0.03	-0.03	-0.05	0.01	-0.01
premium23	-0.06	0.14	-0.10	0.05	0.00	-0.02	-0.01	0.07	0.09

Note: This table presents standardized regression coefficients from the following specification that is executed separately for each hour:

$Premium_t = \beta_0 + \alpha_1 UMM_t + \gamma_1 Var_{t-1} + \gamma_2 Skew_{t-1} + \delta X_t + \varepsilon_{1t}$

In the regression I use OLS with robust standard errors in order to account for potential heteroscedasticity problems. Highlighted coefficients (bold) indicate significance with p < 0.1.

Table A6. Impact of messages informing about failures on premia

	Marg.	*Base.*	*Sk.*	*Var.*	*Mon*	*Tue*	*Wed*	*Fri*	*Sat*	*Sun*
premium0	0.00	**-0.07**	-0.04	0.01	0.06	0.04	**0.08**	0.04	0.02	**0.08**
premium1	0.01	-0.04	**0.08**	0.00	**0.08**	**0.07**	0.06	0.06	0.05	**0.08**
premium2	0.03	**-0.06**	-0.04	0.04	0.04	0.01	0.05	0.05	0.00	**0.08**
premium3	0.02	-0.02	**-0.09**	0.09	0.07	0.01	0.05	0.06	-0.01	0.03
premium4	0.01	-0.04	-0.06	0.05	0.09	0.03	0.06	0.03	-0.01	0.04
premium5	0.04	0.00	0.07	-0.17	0.08	0.06	0.05	0.01	0.06	0.08
premium6	0.00	-0.01	-0.03	-0.15	0.05	0.03	0.02	0.00	0.13	0.15
premium7	**-0.09**	0.00	-0.02	-0.06	0.00	-0.04	-0.03	0.00	0.11	0.12
premium8	**-0.12**	-0.02	-0.17	0.05	-0.03	-0.05	-0.03	-0.02	0.10	0.12
premium9	**-0.12**	**-0.07**	0.16	-0.21	-0.05	-0.06	-0.06	-0.04	0.07	0.09
premium10	**-0.10**	**-0.09**	**0.36**	**-0.41**	-0.07	0.00	-0.02	-0.04	0.08	0.10
premium11	**-0.08**	**-0.08**	0.42	**-0.55**	-0.01	-0.02	0.01	-0.02	0.08	0.11
premium12	**-0.09**	**-0.10**	**0.50**	**-0.58**	-0.01	-0.01	0.04	-0.02	0.06	0.12
premium13	**-0.10**	**-0.06**	**0.50**	**-0.62**	-0.04	-0.06	-0.03	-0.02	0.04	0.09
premium14	**-0.07**	-0.04	**0.48**	**-0.58**	-0.06	-0.04	0.01	0.00	0.07	0.10
premium15	-0.06	-0.02	0.66	-0.73	0.00	-0.01	0.05	-0.03	0.05	0.08
premium16	-0.06	-0.03	-0.01	0.48	-0.05	-0.06	-0.04	-0.08	-0.01	0.01
premium17	**-0.08**	-0.04	-0.03	0.56	-0.02	-0.03	-0.02	-0.04	0.03	0.04
premium18	**-0.07**	-0.04	0.08	-0.34	-0.08	-0.06	-0.02	0.03	0.02	0.05
premium19	**-0.14**	**-0.06**	0.19	-0.14	-0.02	-0.03	-0.01	0.02	0.06	0.06
premium20	**-0.15**	**-0.09**	0.17	-0.11	-0.05	-0.02	0.00	0.00	0.05	0.03
premium21	**-0.06**	-0.01	0.22	-0.33	0.01	0.00	0.03	-0.02	0.08	0.08
premium22	**-0.12**	**-0.07**	0.18	-0.23	-0.02	-0.03	-0.03	-0.04	0.01	0.00
premium23	-0.06	-0.03	**0.14**	-0.10	0.05	0.00	-0.01	0.00	0.08	0.09

Note: This table presents standardized regression coefficients from the following specification that is executed separately for each hour:

$$Premium_t = \beta_3 + \alpha_6 Marg_t + \alpha_7 Base_t + \gamma_7 Var_{t-1} + \gamma_8 Skew_{t-1} + \delta_4 X_t + \varepsilon_{3t}$$

In the regression I use OLS with robust standard errors in order to account for potential hetero-scedasticity problems. Highlighted coefficients (bold) indicate significance with $p < 0.1$.

Table A7. Impact of messages informing about failures on premia

	Failure	*Sk.*	*Var.*	*Mon*	*Tue*	*Wed*	*Fri*	*Sat*	*Sun*
premium0	**-0.07**	-0.04	0.01	**0.07**	0.04	**0.09**	0.04	0.02	**0.08**
premium1	**-0.05**	**0.08**	0.00	**0.09**	**0.07**	0.06	0.06	0.05	0.08
premium2	-0.04	-0.04	0.04	0.04	0.01	0.05	0.05	0.01	**0.08**
premium3	-0.02	**-0.09**	0.09	**0.08**	0.01	0.05	0.06	-0.01	0.03
premium4	-0.02	-0.06	0.05	**0.09**	0.03	0.06	0.03	-0.01	0.04
premium5	0.02	0.07	-0.17	0.08	0.06	0.05	0.01	0.06	0.08
premium6	-0.03	-0.03	-0.15	0.05	0.03	0.02	0.00	**0.13**	**0.15**
premium7	**-0.06**	-0.03	-0.06	-0.01	-0.04	-0.04	0.00	**0.11**	**0.12**
premium8	**-0.09**	-0.18	0.05	-0.03	-0.05	-0.04	-0.02	**0.09**	**0.12**
premium9	**-0.13**	0.15	-0.20	-0.05	-0.06	-0.06	-0.04	**0.07**	**0.10**
premium10	**-0.13**	0.35	**-0.40**	-0.06	0.00	-0.02	-0.04	**0.08**	**0.11**
premium11	**-0.09**	0.42	**-0.54**	-0.01	-0.02	0.01	-0.02	**0.09**	**0.12**
premium12	**-0.14**	**0.48**	**-0.57**	-0.01	-0.01	0.04	-0.02	0.06	**0.13**
premium13	**-0.11**	**0.49**	**-0.61**	-0.04	-0.06	-0.03	-0.02	0.04	**0.10**
premium14	**-0.08**	**0.47**	**-0.57**	-0.06	-0.04	0.01	0.00	**0.07**	**0.10**
premium15	-0.05	0.65	-0.73	0.00	-0.01	0.05	-0.03	0.05	**0.09**
premium16	-0.04	-0.01	0.48	-0.05	-0.06	-0.04	-0.08	-0.01	0.01
premium17	**-0.06**	-0.03	0.56	-0.02	-0.04	-0.02	-0.04	0.03	**0.05**
premium18	**-0.09**	0.07	-0.34	-0.08	-0.06	-0.02	0.03	0.02	**0.06**
premium19	**-0.13**	0.19	-0.14	-0.02	-0.03	-0.02	0.01	0.06	**0.07**
premium20	**-0.17**	0.16	-0.10	-0.05	-0.03	-0.01	-0.01	0.05	0.04
premium21	**-0.06**	0.22	-0.33	0.01	0.01	0.03	-0.02	**0.08**	**0.08**
premium22	**-0.14**	0.18	-0.23	-0.02	-0.03	-0.03	-0.05	0.01	0.00
premium23	**-0.07**	**0.14**	-0.10	0.05	0.00	-0.02	-0.01	**0.08**	**0.09**

Note: This table presents standardized regression coefficients from the following specification that is executed separately for each hour:

$$Premium_t = \beta_1 + \alpha_2 Failure_t + \gamma_3 Var_{t-1} + \gamma_4 Skew_{t-1} + \delta_2 X + \varepsilon_{2t}$$

In the regression I use OLS with robust standard errors in order to account for potential hetero-scedasticity problems. Highlighted coefficients (bold) indicate significance with $p < 0.1$.

Table A8. Impact of messages informing about failures on premia

	Coal	*Nuc.*	*Hydro*	*Sk.*	*Var.*	*Mon*	*Tue*	*Wed*	*Fri*	*Sat*	*Sun*
premium0	0.00	**-0.05**	-0.03	-0.04	0.01	**0.07**	0.04	**0.08**	0.04	0.02	**0.08**
premium1	-0.01	-0.04	-0.03	**0.08**	0.00	**0.08**	**0.07**	0.06	0.06	0.05	0.08
premium2	0.01	**-0.05**	-0.03	-0.04	0.04	0.04	0.01	0.05	0.05	0.00	0.08
premium3	-0.02	**-0.07**	0.01	**-0.09**	0.09	**0.07**	0.01	0.05	0.05	-0.01	0.03
premium4	-0.03	**-0.08**	0.01	-0.06	0.05	**0.09**	0.03	0.06	0.03	-0.01	0.04
premium5	0.00	-0.02	0.01	0.07	-0.17	0.08	0.06	0.05	0.01	0.06	0.07
premium6	**-0.04**	0.00	-0.01	-0.03	-0.15	0.05	0.03	0.02	0.00	**0.14**	**0.15**
premium7	**-0.08**	0.02	-0.01	-0.03	-0.06	0.00	-0.04	-0.03	0.00	**0.11**	**0.13**
premium8	**-0.09**	-0.03	-0.02	-0.18	0.05	-0.02	-0.05	-0.03	-0.02	**0.09**	**0.12**
premium9	**-0.08**	-0.02	**-0.09**	0.15	-0.21	-0.04	-0.06	-0.06	-0.04	**0.07**	**0.10**
premium10	**-0.08**	-0.03	**-0.09**	0.35	**-0.41**	-0.06	0.00	-0.02	-0.04	**0.08**	**0.11**
premium11	**-0.06**	0.00	**-0.06**	0.42	**-0.55**	-0.01	-0.02	0.02	-0.02	**0.09**	**0.12**
premium12	**-0.08**	0.00	**-0.10**	**0.49**	**-0.57**	0.00	-0.01	0.04	-0.01	**0.06**	**0.14**
premium13	**-0.11**	-0.01	-0.05	**0.49**	**-0.62**	-0.03	-0.06	-0.03	-0.02	0.04	**0.10**
premium14	**-0.05**	**-0.04**	-0.03	**0.48**	**-0.58**	-0.06	-0.04	0.01	0.00	**0.07**	**0.10**
premium15	-0.05	-0.04	0.01	0.66	-0.74	0.00	-0.01	0.05	-0.03	0.05	**0.09**
premium16	-0.03	-0.01	0.00	-0.01	0.47	-0.05	-0.06	-0.04	-0.08	-0.01	0.02
premium17	**-0.06**	0.00	-0.02	-0.03	0.56	-0.02	-0.04	-0.02	-0.04	0.03	**0.05**
premium18	**-0.06**	0.01	**-0.06**	0.08	-0.34	-0.08	-0.06	-0.02	0.03	0.02	**0.06**
premium19	**-0.11**	0.01	**-0.06**	0.19	-0.15	-0.02	-0.03	-0.01	0.02	**0.06**	**0.07**
premium20	**-0.16**	-0.01	**-0.07**	0.17	-0.11	-0.05	-0.02	-0.01	-0.01	0.05	0.04
premium21	**-0.07**	-0.01	-0.02	0.22	-0.33	0.02	0.01	0.03	-0.02	**0.08**	**0.08**
premium22	**-0.14**	**-0.06**	-0.04	0.18	-0.23	-0.02	-0.03	-0.03	-0.05	0.01	0.01
premium23	**-0.06**	**-0.05**	-0.02	**0.14**	-0.10	0.05	0.00	-0.01	-0.01	**0.07**	**0.09**

Note: This table presents standardized regression coefficients from the following specification that is executed separately for each hour:

$$Premium_t = \beta_2 + \alpha_3 Coal\ Failure_t + \alpha_4 Nuclear\ Failure_t + \alpha_5 Hydro\ Failure_t + \gamma_5 Var_{t-1} + \gamma_6 Skew_{t-1} + \delta_3 X + \varepsilon_{4t}$$

In the regression I use OLS with robust standard errors in order to account for potential heteroscedasticity problems. Highlighted coefficients (bold) indicate significance with $p < 0.1$.

Table A9. Impact of the size of an outage on premia

	MW	*Sk.*	*Var.*	*Mon*	*Tue*	*Wed*	*Fri*	*Sat*	*Sun*
premium0	**-0.05**	**-0.04**	0.01	**0.07**	0.04	**0.09**	0.04	0.02	**0.08**
premium1	-0.04	**0.08**	0.00	**0.09**	**0.07**	**0.06**	**0.06**	0.05	**0.08**
premium2	-0.04	-0.04	0.04	0.04	0.01	0.05	0.05	0.01	**0.09**
premium3	**-0.04**	**-0.09**	**0.09**	**0.08**	0.02	0.05	**0.06**	-0.01	0.03
premium4	**-0.05**	-0.06	0.05	**0.09**	0.03	**0.06**	0.04	0.00	0.04
premium5	0.00	0.07	-0.17	0.08	0.06	0.05	0.01	0.06	0.07
premium6	-0.03	-0.03	-0.15	0.05	0.03	0.02	0.00	**0.13**	**0.15**
premium7	**-0.05**	-0.03	-0.06	0.00	-0.04	-0.04	0.00	**0.11**	**0.13**
premium8	**-0.09**	**-0.18**	0.05	-0.03	-0.05	-0.03	-0.02	**0.09**	**0.12**
premium9	**-0.12**	0.15	-0.21	-0.04	-0.05	-0.05	-0.03	**0.07**	**0.10**
premium10	**-0.13**	**0.35**	**-0.41**	-0.06	0.00	-0.01	-0.03	**0.08**	**0.12**
premium11	**-0.08**	0.42	**-0.54**	-0.01	-0.02	0.02	-0.02	**0.09**	**0.13**
premium12	**-0.11**	**0.49**	**-0.57**	-0.01	-0.01	0.04	-0.01	**0.06**	**0.14**
premium13	**-0.12**	**0.49**	**-0.62**	-0.03	-0.06	-0.02	-0.02	0.04	**0.11**
premium14	**-0.09**	**0.47**	**-0.58**	-0.06	-0.04	0.01	0.00	**0.08**	**0.10**
premium15	**-0.06**	**0.65**	**-0.73**	0.00	0.00	0.05	-0.03	**0.05**	**0.09**
premium16	-0.03	-0.01	0.48	-0.05	-0.06	-0.04	-0.08	-0.01	0.02
premium17	**-0.05**	-0.03	0.55	-0.02	-0.03	-0.02	-0.04	0.03	**0.05**
premium18	**-0.08**	0.08	-0.34	**-0.08**	-0.06	-0.02	0.03	0.02	**0.06**
premium19	**-0.12**	0.19	-0.15	-0.02	-0.03	-0.01	0.02	**0.06**	**0.07**
premium20	**-0.16**	0.17	-0.11	-0.05	-0.02	0.00	0.00	**0.06**	**0.05**
premium21	**-0.09**	**0.22**	**-0.33**	0.02	0.01	0.04	-0.02	**0.08**	**0.08**
premium22	**-0.15**	0.18	-0.23	-0.02	-0.02	-0.03	-0.05	0.02	0.01
premium23	**-0.10**	**0.14**	-0.10	0.05	0.00	-0.01	0.00	**0.08**	**0.09**

Note: This table presents standardized regression coefficients from the following specification that is executed separately for each hour:

$$Premium_t = \beta_4 + \alpha_8 SizeOfOutage_t + \gamma_8 Var_{t-1} + \gamma_9 Skew_{t-1} + \delta_5 X + \varepsilon_{4t}$$

In the regression I use OLS with robust standard errors in order to account for potential hetero-scedasticity problems. Highlighted coefficients (bold) indicate significance with $p < 0.1$. MW indicates size of the outage and the unit of measurement is 100 MW.

Table A10. Existence of premia and market-specific news and their impact on premia

Premia	*Const.(1)*	*UMM(2)*	*Marginal(3)*	*Base(4)*
Premium h0	0.891	-0.702	-0.108	-0.574
	(0.105)***	(0.219)**	(0.232)	(0.211)**
Premium h1	1.360	-0.719	-0.134	-0.546
	(0.111)***	(0.234)**	(0.233)	(0.221)*
Premium h2	1.594	-0.692	0.153	-0.729
	(0.125)***	(0.262)**	(0.281)	(0.245)**
Premium h3	1.761	-0.458	-0.049	-0.339
	(0.123)***	(0.256)	(0.264)	(0.255)
Premium h4	1.531	-0.507	-0.081	-0.534
	(0.120)***	(0.250)*	(0.253)	(0.242)*
Premium h5	0.592	0.444	0.530	0.087
	(0.222)**	(0.668)	(0.400)	(0.415)
Premium h6	-0.530	0.038	-0.213	-0.120
	(0.196)**	(0.558)	(0.393)	(0.397)
Premium h7	-2.653	-0.875	-1.332	-0.122
	(0.289)***	(0.783)	(0.572)*	(0.586)
Premium h8	-3.122	-1.264	-2.195	-0.318
	(0.275)***	(0.647)	(0.580)***	(0.573)
Premium h9	-3.460	-2.484	-1.327	-1.349
	(0.266)***	(0.429)***	(0.549)*	(0.534)*
Premium h10	-3.847	-2.700	-1.416	-2.113
	(0.293)***	(0.484)***	(0.583)*	(0.580)***
Premium h11	-4.612	-2.116	-1.493	-1.757
	(0.318)***	(0.632)***	(0.665)*	(0.593)**
Premium h12	-3.230	-1.588	-1.289	-1.091
	(0.224)***	(0.487)**	(0.407)**	(0.440)*
Premium h13	-2.545	-1.248	-1.054	-0.452
	(0.207)***	(0.448)**	(0.385)**	(0.396)
Premium h14	-1.952	-1.078	-0.772	-0.184
	(0.190)***	(0.347)**	(0.362)*	(0.378)
Premium h15	-1.515	-0.612	-0.257	-0.041
	(0.205)***	(0.391)	(0.432)	(0.374)
Premium h16	-1.014	-3.094	-1.730	0.030
	(0.778)	(1.986)	(1.644)	(1.033)

Premium h17	-2.844	-3.520	-3.244	-0.378
	(0.895)**	(1.905)	(1.896)	(1.336)
Premium h18	-3.791	-1.905	-1.600	-0.535
	(0.325)***	(0.639)**	(0.592)**	(0.649)
Premium h19	-2.321	-1.762	-1.561	-0.748
	(0.193)***	(0.391)***	(0.355)***	(0.360)*
Premium h20	-1.361	-1.521	-1.250	-0.869
	(0.140)***	(0.263)***	(0.242)***	(0.277)**
Premium h21	-0.935	0.030	-0.394	0.028
	(0.134)***	(0.578)	(0.266)	(0.290)
Premium h22	-0.790	-0.851	-0.840	-0.567
	(0.111)***	(0.261)**	(0.190)***	(0.229)*
Premium h23	0.040	-0.414	-0.392	-0.106
	(0.090)	(0.225)	(0.181)*	(0.186)

Note: This table presents results from regressions which details are provided below.

Column 1 reports the evolution of the average difference between the day-ahead and the intra-day price - the premium over a day. Column 2 reports coefficient $\alpha_1$from the equation

$$Premium_t = \beta_0 + \alpha_1 UMM_t + \gamma_1 Var_{t-1} + \gamma_2 Skew_{t-1} + \delta X_t + \varepsilon_{1t}$$

Columns 3 and 4 report coefficients α_6 and α_7 from equation

$$Premium_t = \beta_3 + \alpha_6 Marg_t + \alpha_7 Base_t + \gamma_7 Var_{t-1} + \gamma_8 Skew_{t-1} + \delta_4 X_t + \varepsilon_{3t}$$

In all regressions OLS with robust standard errors is used separately for each hour. Variables UMM, Marginal and Base are zero-one variables with 0 when there is no news informing about particular type of failure in the hour and 1 in the opposite case.

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table A11. Impact of messages informing about failures on premia

Premia	*Failure (1)*	*Failure coal (2)*	*Failure nuclear (3)*	*Failure hydro (4)*
Premium h0	-0.576	0.059	-0.823	-0.246
	(0.207)**	(0.284)	(0.363)*	(0.246)
Premium h1	-0.444	-0.016	-0.618	-0.309
	(0.220)*	(0.269)	(0.410)	(0.248)
Premium h2	-0.495	0.033	-0.872	-0.347
	(0.249)*	(0.326)	(0.431)*	(0.270)
Premium h3	-0.159	-0.163	-1.273	0.171
	(0.246)	(0.307)	(0.402)**	(0.290)

Premium h4	-0.271	-0.229	-1.501	0.014
	(0.240)	(0.286)	(0.420)***	(0.273)
Premium h5	0.324	0.036	-0.621	0.247
	(0.508)	(0.392)	(0.427)	(0.354)
Premium h6	-0.204	-0.659	-0.003	-0.161
	(0.429)	(0.382)	(0.509)	(0.337)
Premium h7	-0.582	-1.504	0.962	0.061
	(0.653)	(0.590)*	(0.634)	(0.534)
Premium h8	-1.115	-1.946	-0.840	-0.503
	(0.608)	(0.607)**	(0.821)	(0.550)
Premium h9	-2.256	-1.370	-0.252	-1.539
	(0.462)***	(0.626)*	(0.794)	(0.626)*
Premium h10	-1.938	-1.232	-0.941	-2.175
	(0.512)***	(0.657)	(0.854)	(0.615)***
Premium h11	-1.467	-1.351	0.043	-1.442
	(0.589)*	(0.713)	(0.880)	(0.652)*
Premium h12	-1.203	-1.362	0.040	-1.357
	(0.450)**	(0.473)**	(0.534)	(0.445)**
Premium h13	-1.030	-1.697	-0.140	-0.493
	(0.433)*	(0.435)***	(0.513)	(0.407)
Premium h14	-0.548	-0.713	-0.764	-0.143
	(0.430)	(0.381)	(0.459)	(0.373)
Premium h15	-0.926	-0.477	-1.027	0.271
	(0.308)**	(0.420)	(0.510)*	(0.412)
Premium h16	-1.844	-1.129	-1.460	1.372
	(1.142)	(1.218)	(1.149)	(1.197)
Premium h17	-2.487	-2.907	-0.230	-0.368
	(1.293)	(1.608)	(1.518)	(1.398)
Premium h18	-1.746	-1.146	0.344	-1.153
	(0.540)**	(0.711)	(0.647)	(0.604)
Premium h19	-1.187	-1.120	0.155	-0.508
	(0.388)**	(0.390)**	(0.450)	(0.372)
Premium h20	-1.024	-1.446	-0.222	-0.561
	(0.271)***	(0.275)***	(0.312)	(0.280)*
Premium h21	0.071	-0.494	-0.157	-0.188
	(0.390)	(0.256)	(0.292)	(0.264)
Premium h22	-0.430	-0.934	-0.610	-0.407
	(0.310)	(0.215)***	(0.265)*	(0.216)

Premium h23	-0.364	-0.400	-0.501	-0.017
	(0.197)	(0.181)*	(0.237)*	(0.182)

Note: This table presents results from regressions which details are provided below.

Column 1 shows coefficient α_2 from equation

$Premium_t = \beta_1 + \alpha_2 Failure_t + \gamma_3 Var_{t-1} + \gamma_4 Skew_{t-1} + \delta_2 X + \varepsilon_{2t}$

Columns 2, 3 and 4 show coefficients α_3, $\alpha_4$and $\alpha_5$from equation

$Premium_t = \beta_2 + \alpha_3 Coal\ Failure_t + \alpha_4 Nuclear\ Failure_t + \alpha_5 Hydro\ Failure_t + \gamma_5 Var_{t-1} + \gamma_6 Skew_{t-1} + \delta_3 X + \varepsilon_{4t}$

In all regressions OLS with robust standard errors is used separately for each hour. Variables Failure, Failure coal, Failure nuclear and Failure hydro are zero-one variables with 0 when there is no news informing about particular type of failure in the hour and 1 in the opposite case.

* p<0.05; ** p<0.01; *** p<0.001

Chapter 3

Strategic withholding through production failures*

Abstract: Anecdotal evidence indicates that electricity producers use production failures to disguise strategic reductions of capacity in order to influence prices, but systematic evidence is lacking. We use an instrumental variables approach and data from the Swedish energy market to examine such behavior. In a market without strategic withholding, the decision to report a failure should be independent of the market price. We show that marginal producers base the decision to report a failure, in part, on prices, which indicates that failures are a result of economic incentives as well as of technical problems.

* This paper is a joint work with Sara Fogelberg (Stockholm University and IFN). We are grateful for comments from Richard Friberg, Mårten Palme, Mikael Priks, Thomas Tangerås, Pär Holmberg, Sven-Olof Fridolfsson, John Kwoka, Estelle Cantillon, Erik Lindqvist, Yoichi Sugita and Johanna Rickne as well as seminar participants at Stockholm School of Economics and Research Institute of Industrial Economics (IFN), conference participants at YEEES 2013 in Stockholm and seminar participants at ECARES. The work has been financially supported by the research program *The Economics of Electricity Markets*.

- We decided the prices were too low... so we shut down.
- Excellent. Excellent.
- We pulled about 2,000 megs of the market.
- That's sweet.
- Everybody thought it was really exciting that we were gonna play some market power. That was fun!

Intercepted exchange between Reliant traders, June 2000, Weaver (2004)

3.1. Introduction

A competitive and well-functioning market is one of the goals of modern, liberalized electricity markets. However, a commonly voiced concern has been that firms strategically reduce their generating capacity in order to increase the electricity price. Strategic withholding of electricity was, for example, observed during the electricity crisis in 2000-2001 in California, and has been determined to be one of the reasons why the crisis became so severe (Kwoka and Sabodash 2011, Weaver 2004). Theoretical studies have also shown how firms benefit from this behavior (Crampes and Creti 2005, Kwoka and Sabodash 2011). On the other hand, studies of market power investigating the Nordic electricity market Nord Pool have so far been inconclusive (Vassilopoulous 2003, Hjalmarsson 2000, Fridolfsson and Tangeras 2009).

In this article we look at a previously unexamined method that electricity producers can use to withhold capacity in order to increase prices on the Nordic electricity market. We consider instances when generators shut down part of their production due to a failure, and we verify whether the decision to stop production and inform about this failure depends on economic incentives rather than being the result of a technical problem. Market participants on Nord Pool are obliged to publicly inform about changes to consumption, generation or transmission that exceed 100MW and last longer than 60 minutes in so-called Urgent Market Messages (UMMs). We investigate whether spot prices on Nord Pool influence the probability of production failures being reported in UMMs. A decision about reporting a failure should be independent of prices, as failures should be irregular and difficult to foresee. Detection of a significant relationship between prices and market messages therefore indicates that market participants base decisions concerning reporting a failure not only on technical problems, but also on economic incentives.

We use a unique dataset containing UMMs released by market participants with information about planned and unplanned reductions in production. Our dataset permits us to examine how prices affect market participants' decision about issuing failure messages and how this decision varies by the type of generator. We distinguish messages issued by different types of baseload unit production (nuclear and hydro[46]), and marginal unit production (coal, gas and oil). When the demand is high, a small reduction in produced quantity can have a large impact on prices, and this reduction can be achieved by either a marginal or baseload unit. However, a producer with several types of generators primarily has an incentive to decrease production for marginal fuel types, as these production units have higher marginal costs. We hence expect larger effects for marginal fuel types which, in the case of Sweden, are oil, gas and coal.

We also separate the effects for new messages regarding failures and follow-up messages concerning already reported failures. This distinction is important as the incentives might differ depending on whether a producer decides on the new failure or on the prolongation of an existing outage. It is possible that a generator decides to report a new failure based on the encountered technical problems, but that the decision on the length of the failure depends on economic incentives. An increased number of follow up messages indicates that it takes longer to fix a failure, and the time it takes to fix a failure should not depend on prices in a competitive market.

[46] Although hydro generation, especially with reservoirs, can be thought of as marginal type of generation due to its fast response time and balancing characteristics, in this analysis we treat hydro as baseload. We make a distinction between types of electricity generation with regard to the level of marginal costs as low costs generators will face different incentives than high cost generators.

We use a linear two-step model where we estimate the effect of prices on the number of UMMs being released on a certain day. Because of problems of endogeneity between prices and failures reported in UMMs, we instrument for prices using daily temperatures. For instance, prices could affect how generators are operated, which could also affect failure rates. Temperature was chosen as an instrument due to its exogenous nature and because prices on the Nordic electricity market are highly correlated with temperature; especially during the cold season, when electricity is used for heating, temperature and demand follow each other closely.

To our knowledge, this is the first article studying strategic withholding that uses a quasi-experimental set up. The results indicate that there is a significant relationship between day-ahead electricity prices and the number of reported failures. The size of the effect depends on the type of fuel used for generation. We find a positive effect of an increase in price on the number of reported failures in the case of marginal technologies (oil and gas). This is consistent with the hypothesis that it is more profitable to withhold capacity from generators with a high marginal cost. The results also show that prices have a larger effect on follow-up messages compared to messages reporting an initial failure.

We first describe the economic rationale for withholding capacity in Section 2 of this chapter, followed by a description of the Nordic electricity market in Section 3. The data used in the analysis is presented in Section 4. Section 5 presents the econometric strategy and results are discussed in Section 6. The last section concludes.

3.2. Economic rationale for withholding capacity

Strategic withholding is regarded as a way of exploiting market power on electricity markets. A multi-unit generator that wants to increase the market price can achieve it in two ways. It can either strategically bid all of its production, asking for high prices (above its marginal costs[47]), or it can physi-

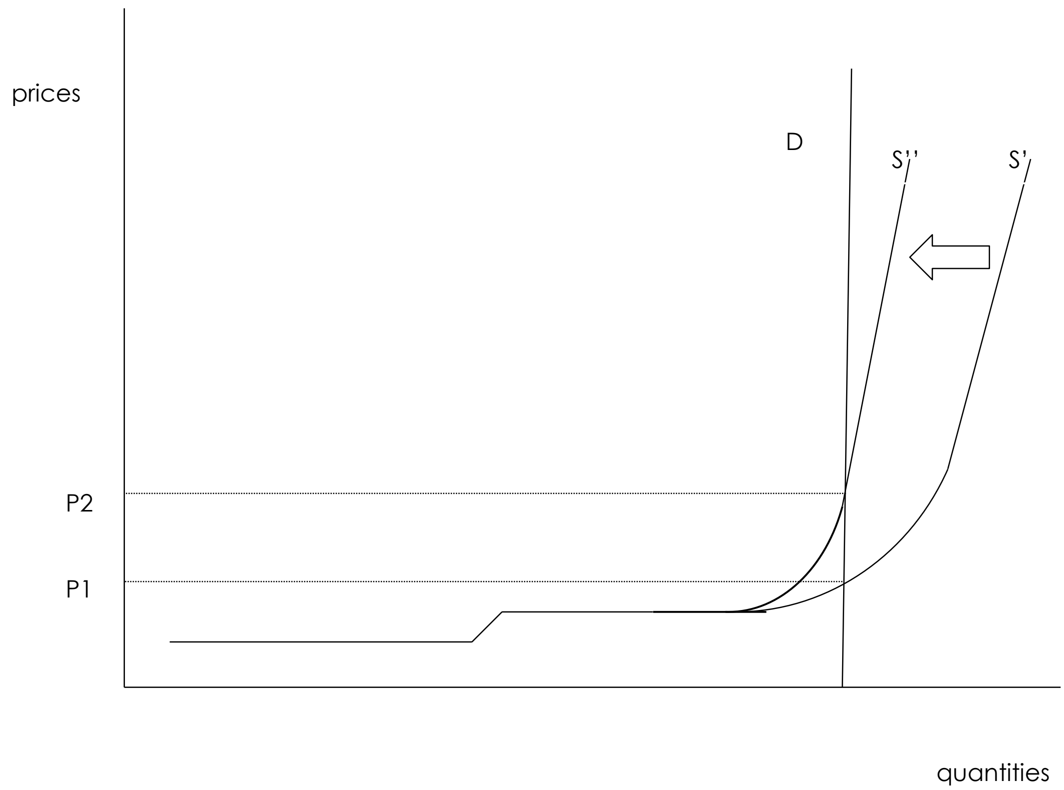
[47] This form of capacity withholding is often referred to as "economic withholding" Moss (2006).

cally keep some of its capacity away from the market.[48] This article deals with a specific version of physical withholding - the reduction in capacity through production failure. Here, and in the relevant literature, "strategic" is not defined as an interaction between multiple market players, but as a unilateral decision of one player to systematically influence prices (Wolfram 1998, Kwoka and Sabodash 2011). Another important distinction is that even though strategic withholding is considered as uncompetitive behavior, and a form of market power abuse, an individual firm engaging in this behavior does not need to possess large market share for withholding to be advantageous (Kwoka and Sabodash 2011, Kwoka 2012). In order for the strategic withholding to be profitable, a producer needs to own several production units and the increase in profit after a production failure needs to be larger than the lost profit from the withheld generation.

Figure 1 illustrates physical withholding behavior and its intended impact on prices. The graph depicts characteristics of a liberalized wholesale electric power market with inelastic demand (in the short run) and a hockey-stick shaped supply curve. The special shape of the supply curve is due to the merit order of electricity production, that is, the ordering of electricity production technologies according to their increasing marginal cost of production. Electricity is supplied by either baseload production with large starting costs but low, almost zero, marginal cost (for instance, through nuclear power plants), or by marginal production that starts producing when the baseload cannot fulfill the demand (for instance, coal or gas in the Nordic energy market). Moreover, different plants have some fixed capacity with steady costs that rise sharply when this capacity is exceeded.

[48] For the first alternative see for e.g. Wolfram (1998) where it is shown that in England large suppliers bid strategically above their marginal costs and that all power plants submit higher bids if their owner has more low-cost capacity available. Wolfram (1999) has as well evaluated prices in the spot market, comparing several price-cost ratios with the outcomes of theoretical oligopoly models and concluded that capacity withholding did not result in as high markups as the theory would suggest.

Figure 1. Wholesale electricity market, capacity withholding.



The Nordic electricity market operates as a uniform auction, resulting in a single equilibrium price for each hour. A reduction of supplied quantity shifts the supply curve to the left, which can result in big price changes, especially if the demand curve is close to the almost vertical part of the supply curve. This explains why even producers with a small share of the market can gain from strategic withholding if the demand is high.

We expect different production technologies to have different incentives for strategic withholding and we anticipate finding larger effects for marginal production technologies. Withholding marginal production is more profitable, as these units have higher marginal costs compared to baseload units. When demand is high and marginal production units set the price, even a small reduction of capacity can have a substantial impact on prices. Under these circumstances the market price is higher than the marginal cost of baseload production so it is in one's interest to utilize cheap, baseload production. For technical reasons it is also easier to shut down a marginal production unit compared to a baseload production unit. In the Nordic electricity market, we expect larger effects for coal, gas and oil, since these are considered marginal technologies.

3.2.1. Strategic withholding through failures

In contrast to the withholding literature that focuses on bidding strategies of operators, we analyze the strategy of physical withholding of capacity. We assume that producers have an incentive for disguising withholding as failures. This strategy, as opposed to simply increasing bid prices, has an advantage of being more difficult to prove simply by looking and comparing bid curves of market participants and can always be explained as being undertaken due to technical reasons or security issues. We assume that disguising capacity withholding as failures can allow firms to claim that they are doing their best in providing generating services under the circumstances. Physical withholding has been examined in the literature concerning price spikes[49] but as Kwoka (2012) points out, the occurrence of extreme price spikes has gone down in most deregulated markets over the last few years. It is possible that the attention that the media and research has brought to the subject has made market participants more careful. There is, however, still the possibility for strategic withholding through production failures given that this strategy is difficult to prove and has not been systematically investigated.

It is possible that there is no systematic timing of failures, but that the time it takes to correct a failure depends on economic incentives. There has been anecdotal evidence of similar behavior played at the British electricity

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[49] Kwoka and Sabodash (2011) develop a method to separate price spikes that are a result from demand shifts under inelastic supply from price spikes that result from strategic withholding. They do this by investigating whether supply systematically shifts down during periods of high demand. They conclude that there is evidence of strategic withholding for a brief period of time during 2001 on the New York wholesale electricity market. They also develop a model that shows that unilateral withholding for a company with two identical production units is profitable, as long as the price increase (resulting from reduction of capacity) is larger than the initial price-cost margin.

pool, where generators have occasionally prolonged the outage if doing so would allow them to receive a higher level of capacity payments (Newbery 1995; Green 2004). In this article we distinguish the effects of failures reported for the first time and of follow-up messages regarding already reported failures. More follow-up messages indicates that it takes longer to fix a failure. If the effects that we estimate are larger for follow-up messages compared to reports of new failures we can conclude that firms put more emphasis on prolonging failures compared to timing them strategically and announcing them for the first time.

3.2.2. Spot prices and timing

By the design of the Nordic electricity market, the next day's electricity prices are set on the previous day at 1 p.m. Prices are correlated over time and in case there are no shocks the expected price for tomorrow's electricity is equal to today's price. Therefore we assume that a producer would base the decision of reporting a failure on today's price. A failure cannot influence the current spot price as this is already fixed. It can however have an impact on the next day's price. Today's production failure will become common knowledge through UMMs. Tomorrow's prices will increase if other producers fail to compensate for this failure. Another scenario assumes that when a failure happens, a more expensive unit produces the missing capacity, which is likely to happen when demand is high. All this will result in today's failure pushing up tomorrow's prices.[50]

In our framework we focus only on the day-ahead market, the spot price, excluding from our analysis possible interactions between markets of different horizons, for instance balancing and future markets. Given our econometric set up we can only estimate how daily variations in price affect failure rates, which means that any long term withholding strategies are outside the scope of this article.

[50] We estimate the impact of failures on the next day's spot price in tables A5 and A6 (see in the Appendix at the end of this chapter).

3.2.3. A Simple Example

In this section we illustrate with simplified calculations how withdrawing of capacity from the market can be a profitable strategy. We use price numbers from our data that we will explore thoroughly later on in this article. We assume that marginal production costs are zero for all types of units.

Consider a producer A, who owns 1000MW production that can be divided into 10 units of 100 MW each. In the warm season, from the 15th of March until the 1st of October, the mean price in our sample is 36€. In order not to lose on withdrawing 100MW of capacity, the price increase as a result to this capacity reduction would need to be at least 4€. If the producer decides not to fail he can earn 36000 € [1000MW*36€]. However, if he decides to fail 100MW, the price would need to be 40€ in order for the producer to enjoy the same profit [900MW*40€=36000€]. The situation is almost the same in the cold period (1st of October – 15th of March) when the mean price is 44€. In this season, the price would need to increase by 4,8€ for the producer to be indifferent to whether or not to reduce capacity by 100MW [44€*1000MW=44000€ vs. 49€*900MW=44100€].

In the time period analyzed, the mean of the difference between today's price and yesterday's price is almost zero and the standard deviation is 5.51€. This indicates that the minimal price change from day to day that is necessary for producer A to not lose on withdrawing capacity (4-5€) is realistic. Moreover, the maximal day to day average price difference observed for the analyzed time frame is 33€.

3.3. Market description

The Scandinavian electricity market is one of the first deregulated electricity markets in the world and the largest European electricity market both in turnover and geographical area. It consists of seven countries belonging to the Nordic and Baltic region (Sweden, Norway, Finland, Denmark, Lithuania, Estonia and Latvia[51]). The market is also connected with other countries including Germany, Poland and the UK. It consists of physical and

[51] http://www.nordpoolspot.com/How-does-it-work/Bidding-areas/

financial markets. Two physical markets form the Nord Pool Spot, and enable trading, one day before the delivery of electricity, on the day-ahead market Elspot, and between 1 to 36 hours before the delivery on the intraday market Elbas. In 2012[52] the total traded volume on Nord Pool reached 432 TWh.[53] Out of this, 334 TWh were traded on Elspot, which was a 13% increase as compared to the volume traded in 2011. 77% of the total consumption of electrical energy in the Nordic market in 2012 was traded through Nord Pool Spot. The Scandinavian market enables trade to many market participants; there are 370 companies from 20 countries trading on Nord Pool.[54]

The day-ahead market is the main arena for electricity trading. Based on bids and offers, a uniform auction determines a unique price that clears the market for each hour. The gate closure for the trades, with delivery for the next day, is 12:00 CET; at around 13:00 CET, prices for the next day are known, and contracts start to be delivered at 00:00 CET. If there is no congestion between the zones, there is the same system price for the entire Nord Pool area, often called the spot price. However, in case of congestion, the market can be divided into up to 15 zones. Each zone can have its own price, which is calculated from the bids and offers submitted to the exchange after taking into account transmission constraints.

Sweden constituted one price area until the 1st of November, 2011, when it was divided into four price zones as a result of an antitrust settlement between the European Commission and the Swedish network operator. There are 29 power plants that are larger than 100MW in Sweden.[55] We summarize their characteristics in Table 1.

[52] http://www.nordpoolspot.com/Global/Download%20Center/Annual-report/annual-report_Nord-Pool-Spot_2012.pdf

[53] This is including the day-ahead auction at N2EX in the UK.

[54] Data from 2012 Nord Pool's yearly rapport.

[55] State on the 4th of December 2012. Source: http://www.nordpoolspot.com/Global/Download%20Center/TSO/Generation-capacity_Sweden_larger-than-100MW-per-unit_06122013.pdf recovered on the 11th of November 2013.

Table 1. Summary characteristics of Swedish electricity production

Areas	*Number of power plants*	*Number of units*	*Main fuel*	*Installed capacity in MW*	*Average size of a unit*
SE1 Luleå	12	21	Hydro	3,764	170.86
SE2 Sundsvall	2	5	Hydro	705	141
SE3 Stockholm	12	24	Oil, Bio, Coal, Nuclear, Gas	11,846	493.58
SE4 Malmö	3	6	Oil, Bio, Gas	1,581	263.5
Total: Sweden	29	56		17,566	313.88

Note: State as on the 4th of December 2012; Source: based on data recovered by author from www.nordpoolspot. com[56]

Power plants are spread unequally across Sweden. There are 12 power plants in the Luleå area – SE1; 2 in the Sundsvall area – SE2; 12 in the Stockholm area – SE3; and 3 in the Malmö area – SE4. The largest installed capacity – 11,846MW - is in the Stockholm area, as this is where Swedish nuclear power plants are based. The number of units is different from the number of power plants as one power plant has between 1 and 4 generating units. There are 6 power plants that have only 1 generating unit in area SE1, 1 in SE2, 4 in SE3, and 2 in SE4.

3.4. Data

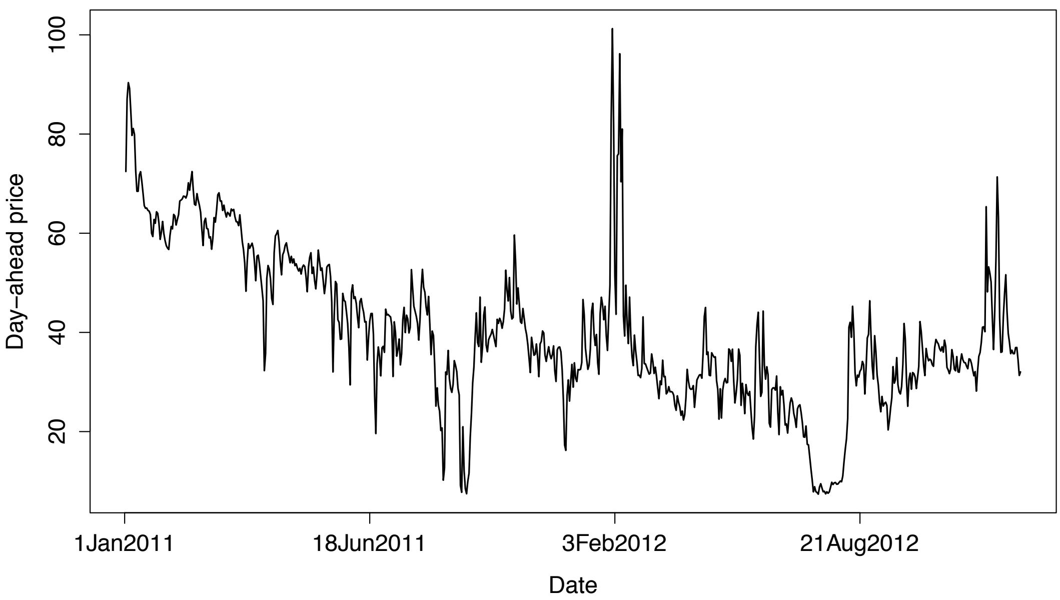
In our analysis we investigate whether market participants report a failure based on the electricity price for the day, t. We examine two years of daily data from the 1st of January, 2011, to the 31st of December, 2012, describing the day-ahead Nordic electricity market Nord Pool. We analyse the Swedish average day-ahead price and we instrument for this price using daily average temperatures in Sweden. The information on all unplanned fail-

[56] Based on the data from: http://www.nordpoolspot.com/Global/Download%20Center/TSO/Generation-capacity_Sweden_larger-than%20100MW-per-unit_04122012.pdf recovered on the 11th of November 2013

ures larger than 100MW and lasting for more than 60 minutes was extracted from the Urgent Market Message dataset. The price data and the Urgent Market Messages (UMMs) are available upon request from Nord Pool's server. The temperature data comes from the Swedish Meteorological and Hydrological Institute (SMHI).

3.4.1. Price and temperature data

Figure 2. Swedish average Elspot price



The evolution of the Swedish average day-ahead price is depicted in Figure 2.[57] The data sample starts with high prices above 80€/MWh during the winter of 2011. The price gradually decreases before again peaking in February 2012 when prices for two days exceeded 90€/MWh. Prices rose again in December 2012. From the 1st of November, 2011, Sweden has been

[57] Scrutinizing the price graph could raise doubts whether the price time series is stationary. Therefore we test the null hypothesis that the price data follows a unit root process with the use of the Dickey-Fuller test. We reject the null hypothesis and conclude that the series is stationary.

divided into four price areas; for the purpose of the analysis in this article we construct and use an average price for the whole country. Table 2 reports summary statistics describing price distribution.

Table 2. Summary statistics describing the Swedish average day-ahead price

Variable	*Heating Season*	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*
Swedish price		731	40.08	15.6	7.37	101.26
Swedish price	Yes	333	44.29	15.96	7.46	101.26
Swedish price	No	398	36.55	14.39	7.37	68.16
Log of Swedish price		731	3.6	0.46	2	4.62
Log of Swedish price	Yes	333	3.72	0.38	2.01	4.62
Log of Swedish price	No	398	3.5	0.49	2	4.22

Note: This table presents summary statistics for the day-ahead Swedish electricity price from the Scandinavian electricity market Nord Pool during the period from the 1st of January 2011 to the 31st December 2012. Variable *Swedish price* is reported in Euros per megawatt hour. Variable *Log of Swedish price* is a natural logarithm of Swedish price. From the 1st if November 2011 Sweden has been divided into four price areas; for the purpose of this analysis we construct and use an average price for the whole country. The heating season is defined as the period between the 1st of October and 15th of March; in general this is the period when the demand is higher as a significant share of heating in Sweden is electrical.

The overall mean price for Swedish electricity traded at Nord Pool is 40€/MWh. The difference between the highest and the lowest price is around 94€/MWh. The cold season, between October and the middle of March, is characterised by higher mean prices that oscillate around 44€/MWh. In the rest of the year, average prices are lower, at around 36€/MWh, with the highest mean price of 68€/MWh registered in the second part of March 2011. As we use the natural logarithm of price instead of levels, in Table 2 we also report the summary statistics for the transformed price variable – the Swedish price log. Figure A1 in the appendix plots the log of the day-ahead Swedish spot price.

In our analysis we use an average temperature for Sweden to instrument for the price. The mean temperature in the analysed period is 4.26

Celsius. The coldest period was in February 2011 when the average temperature dropped to -20 Celsius. Table 3 presents summary statistics for the temperature data for the Swedish average temperature recorded between the 1st of January, 2011 and the 31st of December, 2012.

Table 3. Summary statistics describing the Swedish average temperature

Variable	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*
Temperature	731	4.26	8.16	-21.18	19.56

Note: This table presents summary statistics for the Swedish average temperature recorded between the 1st of January 2011 and the 31st December 2012.

There is an expected negative correlation of -0.47 between the price variable and the temperature indicating that when the temperature drops the electricity price increases.

3.4.2. The UMM dataset

The Urgent Market Messages dataset is composed of messages informing about all planned and unplanned outages exceeding 100MW and lasting for more than 60 minutes that were recorded in the Nord Pool area. We measure the number of failures (the unplanned outages per day) as the variable $Failure_t$. Based on the information extracted from the UMMs we were able to identify the area that would potentially be most affected by the event that the message was informing about. The affected area is identified by the issuer of the message. In our two-year sample there are 1,327 messages announcing failures affecting Sweden; out of these, 618 are hydro failures, 341 are nuclear failures, 99 are gas failures, 75 are oil failures, 41 are biofuel failures, and only 4 are coal production failures.

In the Nordic area the demand for electricity rises as it gets colder. The calendar year can be roughly divided into two seasons: the heating season from the 1st of October to the 15th of March, and the warmer season without heating, covering the rest of the year. As the demand increases, the production required to meet this demand also rises. Marginal types of production are not constantly employed but are started when the high level of demand requires additional capacity. Therefore it is possible that certain types of production report unplanned outages only in winter when the heating is turned on. To show that this is not the case in Table 4 we report the number of registered messages informing about failures during the heating season (when prices are generally high) and in the off-heating season (when prices are, on average, low).

Table 4. Number of messages reporting failures per fuel type

Variable	Heating Season			Off Heating Season			Whole year	Heating Season	Off Heating Season
Production type	All failures	New failures	Follow-up failures	All failures	New failures	Follow-up failures	All failures	% of follow-ups	% of follow-ups
All	735	264	471	592	592	200	1345	64	34
Nuclear	151	39	112	190	39	151	341	74	79
Hydro	333	144	189	285	118	161	618	56	56
Coal	4			0			4		
Oil	56	24	32	19	9	10	75	57	52
Gas	58	19	39	41	13	28	99	67	68

Note: The heating season is defined as the period between the 1st of October and 15th of March. Last column is the summation of all messages of different fuel type over the studied sample.

The data indicates that failure messages were reported in both seasons with the exception of coal fueled electricity generation that has issued only 4 messages informing about problems affecting Sweden. Subsequently we dropped coal failures from further analyses.

An important remark is that the number of UMMs informing about failures is not necessarily equal to the number of actual failures. Market participants can issue multiple UMMs addressing the same failure, defined as so-called follow-up messages. In such a case, each message will bring additional information about the same event. Therefore, in order to make a distinction between the number of actual failures and messages that describe the same failure several times, we created $NewFailure_t$ and $FollowupFailure_t$

variables. The first counts the actual number of failures, and the latter counts the number of follow-up messages. In the studied sample there were 464 new failures registered by different types of electricity production; the rest (863) were follow-ups.

3.5. Empirical strategy

We are interested in studying the effect of price on the decision to report a failure by an electricity producer. We define a failure as a number of announcements informing about unplanned outages affecting Sweden per day, which are reported through UMMs. Price is the day-ahead Swedish electricity price for day *t* set at *t-1*. There are two concerns with estimating such a relationship with the use of a simple OLS. First, "failure" is not normalized which means that number of failures could naturally increase with the production level, and the production level is also correlated with price. In order to overcome this issue we control for aggregated bid production, which is the market clearing aggregated production level for day *t* based on *t-1* bids. We use aggregated bid production for each day, instead of that day's realized production, because real time production is endogenous in relation to failures. In order to capture any potential non-linear effects we use a set of dummies for different levels of bid production.

Second, in an OLS regression we require that $E(error\_term_t|Price_t) = 0$. However, even though $Price_t$ is set on the day before failure is reported, there is a clear risk that different omitted variables such as market players' bidding strategies or technical considerations affect both prices set yesterday and the number of failures today. For instance high prices could encourage producers to run their generators above recommended capacity levels, which would increase the risk of failures. We therefore instrument for prices using daily average temperature for Sweden in a two-stage model:

First stage:

$$LogPrice_t = \beta_1 Temperature_t + \sum_{i=1}^{4} \beta_{2i}\, BidProduction_t + \sum_{j=1}^{6} \gamma_j W_j + \epsilon_t \quad (1)$$

Second stage:

$$LogFailure_t = \beta_3 \widehat{LogPrice}_t + \sum_{i=1}^{4} \beta_{4i} \ BidProduction_t + \sum_{j=1}^{6} \delta_j W_j + \varepsilon_t \qquad (2)$$

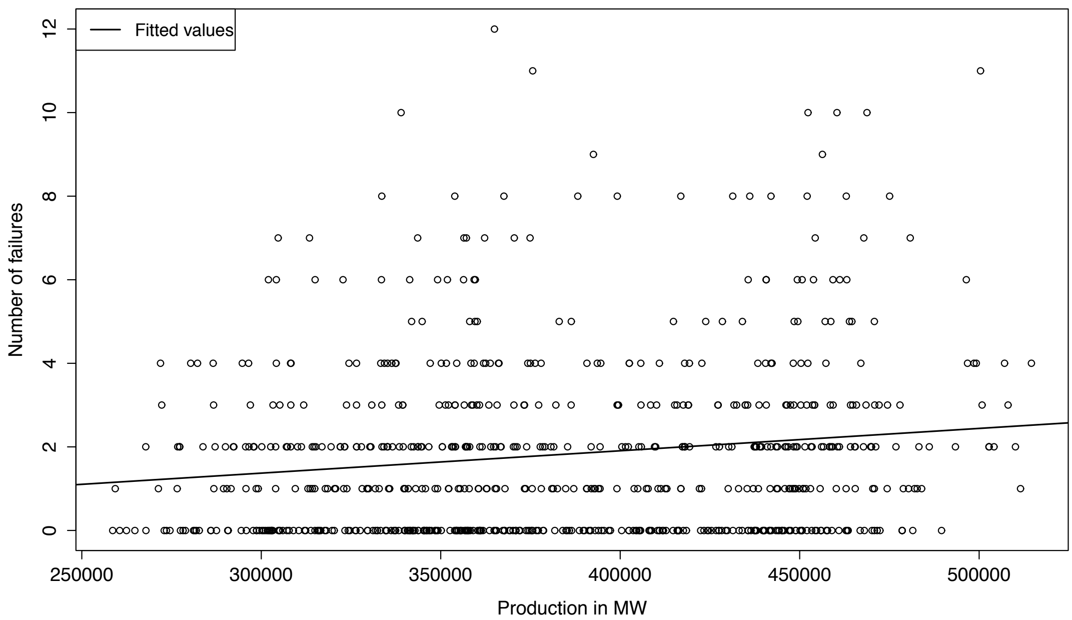
In order to test whether economic incentives affect the timing of new failures or if economic incentives primarily affect the duration of maintenance after a failure we repeat our two-step procedure and estimate separate effects for the newly reported failures and the follow-up messages. Number of follow-up messages is used as a proxy for the length of a failure, as many follow-up messages often indicate a prolonging of a failure or that the failure has increased in size.

As we believe that producers using different production fuels and therefore occupying different places in the merit order have different incentives for withholding, we divide the dependent variable into messages informing about the different fuels. We therefore create four dependent variables that count the number of messages issued by nuclear, hydro, oil and gas generators every day. This division is done for all messages, as well as for the new failures and the follow-up messages. All regressions are done in log-log, meaning that both dependent variables and our variable of interest are logged. We use HAC standard errors in all specifications in order to account for potential heteroskedasticity and autocorrelation issues. We control for the day of the week in the regressions.

The key identifying assumption in order for our instrument to be valid is that conditioned on the control variables, there should be no correlation between temperature and the error term in the equation we wish to correctly estimate. This condition should be satisfied because temperature is strictly exogenous. It is also necessary that there is no direct effect of temperature on the probability of production failures. In the studied period we did not observe any extreme temperatures that would be unfamiliar to Scandinavia. Power plants in the Nordic Region are constructed with the aim of withstanding the normal weather conditions and should not be affected by a normal range of temperatures.

We have identified several potential threats to our identification strategy. First, when temperature decreases additional production units might have to start up in order to cover the increased demand. It is possible that these start-ups influence the probability of failures (a problem that would not affect the results for follow-up messages) or that units that start up when demand is very high are in worse shape, which could potentially influence both failure rates and the time it takes to repair a failure. We do not have data for the number of operating units but we do control for different levels of production in the estimation. This should control for the fact that units of different quality might be used at different levels of production. Further, as can be seen in Figure 3, the relationship between production level and number of failures is only weakly positive. The relationship also seems to be monotonic with no sudden jumps at the highest production levels.

Figure 3. The relationship between bid production and failures



Note: The x-axis shows bid production in MWh and the y-axis shows the number of failures per day registered as affecting Sweden.

Another issue is linked with water temperature. When temperature goes up, water temperature rises as well, which might affect the cooling systems of power plants, potentially reducing a unit's efficiency. The implication of this would be an increased number of failures when temperature increases. In Scandinavia there is an inverse relationship between temperature and prices of electricity; as electricity is used for heating, the demand reaches very high levels when it is cold. Our results indicate that strategic withholding is primarily used when demand is high. This means that any direct effect of warmer water on failure rates would attenuate the results reported in this paper.

An additional concern about the issue of water temperature is linked to the freezing of water reservoirs, which potentially increases the probability of failure of hydro-fueled generators. However, as every UMM contains a description of the reported problem we can manually remove all messages that would indicate that the outage was caused by special weather conditions such as freezing.

The last potential problem that we have identified is linked to the follow-up messages and the length of an outage. If the temperature influences the length of failures (as it might be harder to repair failures when it is cold, due to, for example, transportation constraints) we would expect the share of the follow-up messages to be larger during the heating season as compared to the warmer off-heating period. However the percentage of follow-ups announced by nuclear, water, oil and gas-fueled production is constant over the year and there are no large differences between the two seasons (Table 4).

Results of the first stage regression (equation 1) are reported in Table A1 in the Appendix. The high F-statistic of 38 indicates that the temperature is not a weak instrument.

3.6. Results

3.6.1. Results from all messages informing about failures affecting Sweden

The results from the second stage regressions investigating the relationship between the Swedish day-ahead electricity price and the announcement of failure messages are presented below. In Table 5 we focus on all messages reporting failures that were coded as affecting Sweden, issued by Scandinavian producers.[58] The dependent variable measures the log of the number of messages announced on a specific day regardless whether the failures are novel or follow-up messages. The results indicate that a 1% increase in price is associated with a 0.28% increase in the number of reported failures.

[58] In the Appendix table A2 reports results for the same variables of interest estimated with OLS.

Table 5. Failures by fuel type

	All failures	*Nuclear*	*Hydro*	*Oil*	*Gas*
Log of price	0.282	-0.005	-0.009	0.158	0.134
	(2.48)*	(0.07)	(0.10)	(2.79)**	(2.63)**
Production below 300 MWh	-0.560	0.009	-0.065	-0.238	0.137
	(3.48)***	(0.06)	(0.38)	(1.69)*	(3.41)***
Production below 400 MWh	-0.415	0.000	0.024	-0.178	0.115
	(2.73)***	(0.00)	(0.15)	(1.26)	(3.84)***
Production below 500 MWh	-0.381	-0.101	0.107	-0.164	0.140
	(2.57)**	(0.78)	(0.66)	(1.16)	(4.99)***
N	731	731	731	731	731

Note: *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. The regressions include days of the week dummies. T-statistics are in brackets. Daily data. Dependent variable is the log of failures coded as affecting Sweden. Price is the Swedish price in log. With the use of dummies we control for different levels of today's aggregated production based on yesterday's bids. Price is instrumented with temperature.

As we assume that particular technologies used for producing electricity might face different incentives, we disaggregate the failures into outages reported by different fuel types. There are positive and significant results for gas and oil, where a 1% increase in price increases the number of reported failures by 0.134% in the case of gas fueled generation and by 0.16% in the case of oil. There are no significant effects for nuclear or hydro.

3.6.2. Results from new and follow-up messages affecting Sweden

Results for new and follow-up failures (Tables 6 and 7) indicate that the initial announcement of an outage depends less on the encountered price at a particular day compared to the joint effect of new and follow-up messages (Table 5).[59] The results for reporting a failure for the first time are significant for oil and gas fueled plants, for the former type a 1% price increase rises the number of reported failures by 0.1% (Table 6). For gas the effect is smaller.

Table 6. New failures by fuel type

	Failures	*Nuclear*	*Hydro*	*Oil*	*Gas*
Log of price	0.193	0.010	0.016	0.099	0.058
	(2.60)**	(0.33)	(0.27)	(2.70)*	(2.28)*
Production below 300 MWh	-0.209	0.013	-0.086	-0.114	0.040
	(1.34)	(0.19)	(0.75)	(1.34)	(2.29)**
Production below 400 MWh	-0.055	0.021	-0.034	-0.078	0.050
	(0.36)	(0.32)	(0.30)	(0.92)	(3.56)***
Production below 500 MWh	-0.041	0.013	-0.013	-0.074	0.060
	(0.27)	(0.20)	(0.12)	(0.87)	(4.50)***
N	731	731	731	731	731

Note: *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. The regressions include days of the week dummies. T-statistics are in brackets. Daily data. Dependent variable is the log of novel messages informing about failures coded as affecting Sweden. Price is the Swedish price in log. With the use of dummies we control for different levels of today's aggregated production based on yesterday's bids. Price is instrumented with temperature.

The effects on the follow-up messages are larger in magnitude compared to the effects on failures reported for the first time. The general elasticity effect on all follow-up failures aggregated is 0.226 and the effects for oil and gas are 0.105 and 0.108 respectively (Table 7).

[59] In the Appendix in tables A3 and A4 we report results for the same variables of interest estimated with OLS.

Table 7. Follow-up failures by fuel type

	Failures	*Nuclear*	*Hydro*	*Oil*	*Gas*
Log of price	0.226	-0.011	0.001	0.105	0.108
	(2.36)*	(0.18)	(0.01)	(2.65)*	(2.53)**
Production below 300 MWh	-0.502	-0.009	0.022	-0.157	0.112
	(3.21)***	(0.08)	(0.20)	(1.39)	(3.12)***
Production below 400 MWh	-0.406	-0.012	0.093	-0.115	0.090
	(2.71)***	(0.11)	(0.84)	(1.02)	(3.51)***
Production below 500 MWh	-0.380	-0.104	0.154	-0.105	0.105
	(2.59)***	(0.97)	(1.42)	(0.93)	(4.35)***
N	731	731	731	731	731

Note: *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. The regressions include days of the week dummies. T-statistics are in brackets. Daily data. Dependent variable is the log of follow-up messages informing about failures coded as affecting Sweden. Price is the Swedish price in log. With the use of dummies we control for different levels of today's aggregated production based on yesterday's bids. Price is instrumented with temperature.

These findings confirm our hypothesis that the economic incentives are more important when deciding on the scope of a failure - that is, the size and duration of the failure measured through follow-up messages - as compared to the decision of whether to report a new failure.

The effects for both scenarios that we test do not indicate that economic incentives matter for reporting failures in the case of the baseload production. The results for both nuclear and hydro generation are not significant. This finding is not surprising as, due to low marginal costs, the baseload production can recover high infra-marginal profits if the electricity price is established by the marginal units. Reporting a failure when other, more expensive, types of production set the price is not in the economic interest of a cheap producer.

3.7. Conclusions

In this article we investigate whether producers supplying electricity to the Swedish market base their decision of whether to report a failure on economic incentives or on purely technical reasons. The results indicate that prices affect failures reported through Urgent Market Messages in different ways depending on the type of electricity generation. We find no significant effects for the baseload technologies (nuclear and hydro), which suggests that failure risks for baseload technologies do not depend on the daily variations in spot prices. However, we do observe a positive and significant effect of spot prices on the number of reported failures in the case of marginal production generators, which in Sweden are oil and gas.

These findings support the hypothesis that economic incentives play a role when marginal producers decide to report a failure. Small changes to marginal production in periods of high demand can have potentially larger effect on the price levels as compared with similar changes to baseload production in low demand periods. Moreover, producers who own both types of electricity generation (infra-marginal and marginal) are interested in recovering high infra-marginal profits while at the same time decreasing production costs. A strategy to withdraw expensive marginal capacity disguising it as a failure could accomplish these goals.

We see that the effect on follow-up messages is slightly larger in magnitude compared to the effect on failures reported for the first time. This indicates that economic incentives might to a greater degree affect the duration of a failure compared to the probability of reporting a new failure.

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Appendix

Figure A1. The logarithm of the Swedish average Elspot price

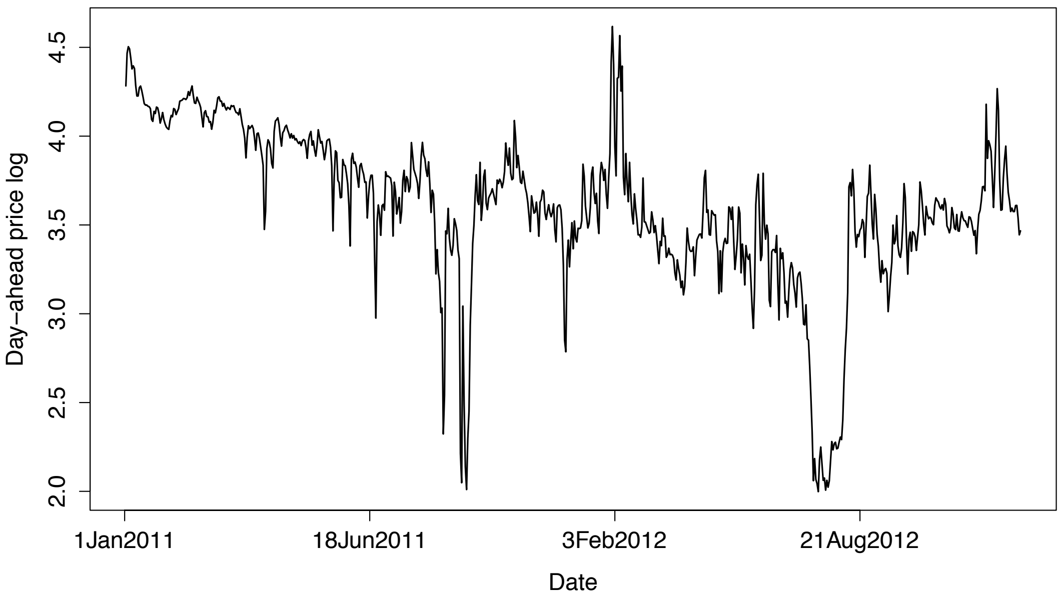

Table A1. First-stage regression

Variable	*Coefficient*	*Robust Std. Err.*	*t*	*P>t*	*95% Conf.*	*Interval*
Production below 300 MWh	0.98	0.079	12.33	0	0.822	1.134
Production below 400 MWh	0.43	0.06	7.06	0	0.308	0.546
Production below 500 MWh	0.09	0.05	1.71	0.087	-0.013	0.184
Temperature	-0.05	0.0026	-17.41	0	-0.051	-0.04

Note: *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. The regressions include days of the week dummies. T-statistics are in brackets. Daily data. Price is the Swedish price in log. With the use of dummies we control for different levels of today's aggregated production based on yesterday's bids. R = 0.36; F (10, 720) = 38.07

Table A2. Failures by fuel type – OLS

	Failure	*Nuclear*	*Hydro*	*Oil*	*Gas*
Price_log	-0.016	-0.096	-0.070	0.056	0.065
	(0.25)	(2.14)**	(1.40)	(2.43)**	(2.73)***
Production below 400 MWh	0.053	-0.036	0.071	0.028	-0.043
	(0.62)	(0.55)	(1.00)	(1.16)	(1.09)
Production below 500 MWh	0.142	-0.121	0.165	0.062	-0.005
	(1.63)	(1.80)*	(2.27)**	(2.32)**	(0.13)
Production below 600 MWh	0.589	0.000	0.071	0.248	-0.130
	(3.69)***	(0.00)	(0.41)	(1.73)*	(3.21)***
R2	0.05	0.04	0.04	0.05	0.03
N	731	731	731	731	731

Note: *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. The regressions include days of the week dummies. T-statistics are in brackets. Daily data. Dependent variable is the log of number of messages informing about failures coded as affecting Sweden. Price is the Swedish price in log. With the use of dummies we control for different levels of today's aggregated production based on yesterday's bids. OLS regression.

Table A3. New failures by fuel type – OLS

	Failure	*Nuclear*	*Hydro*	*Oil*	*Gas*
Price_log	0.007	-0.020	-0.040	0.033	0.031
	(0.17)	(1.02)	(1.23)	(2.26)**	(2.63)***
Production below 300 MWh	-0.228	0.010	-0.091	-0.120	0.037
	(1.44)	(0.15)	(0.80)	(1.38)	(2.10)**
Production below 400 MWh	-0.131	0.009	-0.056	-0.104	0.039
	(0.86)	(0.14)	(0.52)	(1.22)	(3.66)***
Production below 500 MWh	-0.083	0.006	-0.025	-0.088	0.054
	(0.54)	(0.09)	(0.23)	(1.02)	(4.74)***
R2	0.03	0.01	0.02	0.03	0.02
N	731	731	731	731	731

Note: *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. The regressions include days of the week dummies. T-statistics are in brackets. Daily data. Dependent variable is the log of new messages informing about failures coded as affecting Sweden. Price is the Swedish price in log. With the use of dummies we control for different levels of today's aggregated production based on yesterday's bids. OLS regression.

Table A4. Follow-up failures by fuel type – OLS

	Failure	*Nuclear*	*Hydro*	*Oil*	*Gas*
Price_log	-0.019	-0.087	-0.051	0.040	0.051
	(0.37)	(2.12)**	(1.41)	(2.46)**	(2.52)**
Production below 300 MWh	-0.526	-0.017	0.017	-0.163	0.106
	(3.39)***	(0.14)	(0.15)	(1.43)	(2.94)***
Production below 400 MWh	-0.505	-0.043	0.072	-0.142	0.067
	(3.49)***	(0.40)	(0.66)	(1.25)	(3.52)***
Production below 500 MWh	-0.435	-0.121	0.143	-0.120	0.093
	(3.01)***	(1.14)	(1.31)	(1.06)	(4.43)***
R2	0.06	0.04	0.04	0.05	0.04
N	731	731	731	731	731

Note: *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. The regressions include days of the week dummies. T-statistics are in brackets. Daily data. Dependent variable is the log of follow-up messages informing about failures coded as affecting Sweden. Price is the Swedish price in log. With the use of dummies we control for different levels of today's aggregated production based on yesterday's bids. OLS regression.

Table A5. Impact of messages on the price

	price_log	*price_log*	*price_log*	*price_log*	*price_log*	*price_log*	*price_log*
Failure	**0.014**						
	(3.99)***						
Production	0	0	0	0	0	0	0
	(9.31)***	(9.81)***	(9.76)***	(9.71)***	(9.71)***	(9.66)***	(9.77)***
Failure nuclear		-0.02					
		(1.19)					
Failure hydro			-0.001				
			(0.11)				
Failure coal				**0.036**			
				(5.12)***			
Failure oil					0.012		
					(1.28)		
Failure gas						**0.034**	
						(2.91)***	
R2	0.15	0.14	0.13	0.16	0.14	0.14	0.13
N	731	731	731	731	731	731	731

Note: *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. The regressions include days of the week dummies. T-statistics are in brackets. Daily data. Dependent variable is the log price. Failure variables are measuring the number of all failures of certain type registered in Nord Pool per day. Production is measured in MWh.

Table A6. Impact of messages coded as affecting Sweden on the price

	price_log	*price_log*	*price_log*	*price_log*	*price_log*	*price_log*	*price_log*
Failure	-0.001						
	(0.13)						
Swedish Production	0	0	0	0	0	0	0
	(4.41)***	(4.40)***	(4.56)***	(4.37)***	(4.08)***	(4.37)***	(4.50)***
Failure nuclear		**-0.043**					
		(2.12)**					
Failure hydro			-0.017				
			(1.39)				
Failure coal				**0.33**			
				(1.66)*			
Failure oil					**0.086**		
					(3.02)***		
Failure gas						**0.091**	
						(4.40)***	
R2	0.04	0.05	0.04	0.04	0.05	0.05	0.04
N	731	731	731	731	731	731	731

Note: *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. The regressions include days of the week dummies. T-statistics are in brackets. Daily data. Dependent variable is the log price. Failure variables are measuring the number of failures coded as affecting Sweden per day. Production is measured in MWh.

Chapter 4

Private and public information on the Nordic intra-day electricity market*

Abstract: This paper is an empirical investigation of how traders react to public news on the Nordic intra-day electricity market. Using detailed trade information and GARCH models this paper examines market participants' reaction to news about sudden production and transmission failures on the electricity grid. I divide the time of news announcement into three phases: the preannouncement period – the interval up to fifteen minutes before the public announcement of a message, the contemporaneous period – the interval up to fifteen minutes after the announcement of a message, and the post-announcement period – the interval between fifteen to sixty minutes after the announcement of a message. I find that news affects the mean price levels but does not affect volatility. No effect of news on prices and volumes is seen in the preannouncement period, indicating that even if private information exists it is not being used for trading on the intra-day market.

* I am grateful for comments from Richard Friberg, Thomas Tangerås, Pär Holmberg, Johannes Mauritzen, Frank Wolak and participants of the *Performance of Electricity Markets*, IFN Waxholm Conference 2014. The work has been financially supported by the research program *The Economics of Electricity Markets*.

4.1. Introduction

The role of information and its impact on prices and trading is especially important in financial economics. The microstructure literature (O'Hara, 1995; Madhavan, 2000) distinguishes two types of information: private and public. The latter type is the publicly announced news that can be either random (unscheduled) or published at fixed times (scheduled announcements). Private information includes access to not yet released public information (i.e. payoff related private information (Lyons 2000)) or the so called unrelated payoff information that stems from trader's knowledge of the market and its interim states (for e.g. whether there is another trader willing to submit a large trade). There are several types of informed trader; someone who is illegally profiting from fundamental information i.e. an insider trader, or it can be "a trader that is more skilled than other and has superior knowledge based on analysis" (Baker and Kiymaz 2013 p.254). Informed traders can also have superior knowledge about order flow in a security e.g. knowing that a large asset manager will trade a sizable quantity of shares which would result in a price change.

This paper is an empirical investigation of how traders react to public news. I investigate a continuous commodities market with few trades and many unscheduled publicly announced pieces of news. These special characteristics are in contrast to high frequency financial markets where public announcements are rare and usually anticipated.[60] I use price data from the Nordic intra-day electricity market and the dataset of publicly announced Urgent Market Messages that inform about changes to generation, consumption or distribution of electricity that are larger than 100 MW and last for more than 60 minutes.

Market rules are designed to provide full and fair disclosure of all events that have a major impact on the power sector. However, before the information becomes publicly known, there is a period of time when espe-

[60] Examples of studies with few scheduled announcements include Ederington and Lee (1993) who examine the impact of nineteen monthly macroeconomic announcements on the Treasury bond, Eurodollar and deutsche mark futures markets, or Goodhart et al. (1993) where they look at the effect of two news events on the foreign market.

cially generators affected by the event in question have private knowledge about it. Acting on the private information before it becomes public is considered market manipulation and is forbidden according to the Market Conduct Rules[61], which state that participants may not "place, change or remove bids or actively enter into transactions in the market when holding inside information". However, in 2012 alone the Nord Pool Market Surveillance investigated 10 instances of insider trading.[62]

According to the rules governing the disclosure of market news, issuers of messages can act on this information only after it has been made public. However, publishing the information publicly eliminates the private value of information. If public disclosure of information impacts negatively the profitability of the issuer, there exists an incentive to distort or delay the information (von der Fehr, 2013). Using the information for trading just before the news becomes public would allow the issuer to profit from the information prior to it becoming public.

In most analysis of insider trading it is not obvious whether traders have private information. There are studies that look at the proved instances of insider trading and try to verify how these instances affected asset price. Elliot (1984) uses a sample of insider trading instances as so does Meulbroek (1992). In the case that I investigate it can be assumed that generators who bid into the market have perfect information about their condition; they have private information, the question is whether they use it.

I empirically analyze the impact of market news and test for the presence of trades based on private information when there are lots of non-scheduled announcements, often arriving simultaneously. I use a detailed dataset with information about concluded trades and market messages associated with every trade. I evaluate conditional variance models with exogenous variables describing announcement of news.

I find an effect of news on mean price levels but no effect of news on the volatility. The results for both prices and volumes do not show any effects of news in the preannouncement period, indicating that even if private

[61] http://www.nordpoolspot.com/PageFiles/rulebook/MCR.pdf

[62] http://energitilsynet.dk/fileadmin/Filer/Internationalt/Nord_Pool_Spot_REMIT_Seminar.pdf

information exists it is not being used for trading on the intra-day market in a systematic way.

Public and private information and its impact on trading activity has been an important topic in the financial literature. Initially authors concentrated on analyzing the impact of news on trading in the post-announcement period. Ederington and Lee (1993) study the effect of nineteen regularly repeated macroeconomic announcements on the volatility of interest-rates and foreign exchange futures contracts in the US market. Goodhart et al. (1993) investigate the impact of two events on the dollar-sterling exchange rate. Berry and Howe (1994) investigated the impact of many public announcements and their impact on trading volume. Mitchel and Mulherin (1994) looked at large set of public news and their impact on daily trading volume and market returns. This strand of literature focused on the impact of news on trading after the news became public knowledge. However, public information announcement, following the microstructure approach, can help to identify the pre-announcement periods when some individuals might have insider knowledge about the public news prior to its announcement. The separation of traders into those possessing private information and those without it introduces different incentives for timing the trades and therefore can have effects on market activity. Degennero and Shrieves (1997) compare the importance of news and private information as conditioning factors of financial market volatility. They find that high market activity has a positive impact on volatility and spread and they contribute it to traders' private information. Bauwens et al. (2005) study the impact of nine categories of scheduled and unscheduled news on the euro-dollar return volatility and analyze the three time intervals around the announcement of each piece of news. They show that volatility increases in the pre-announcement periods in particular in case of scheduled events and they interpret this as trades done by players who want to make anticipatory trades based on their personal beliefs. The only effect of unscheduled news is observed for the rumors of central bank intervention.

This paper consists of six sections. Section 2 describes the functioning of the Nordic intra-day market and the data. Section 3 discusses the theoretical approaches to thinking about public and private information and their impact on trading. Section 4 presents empirical strategy and results follow in section 5. The final section concludes.

4.2. Market and data description

The Nordic electricity market is composed of physical and financial markets and covers electricity generation in Sweden, Finland, Denmark, Norway, Latvia, Lithuania and Estonia. Two physical markets form the Nord Pool Spot; the larger one, Elspot, enables trading of electricity contracts one day ahead of their physical delivery. The market is supplemented by the intra-day market, Elbas, which operates as a continuous market and enables trading up to one hour before the delivery of electricity. Elbas is a complementary market to the main day-ahead market and handles around 1% of electricity as compared with Elspot, but it is constantly growing. In 2010[63] Elbas turnover was slightly above 2TWh, rising to 2.5TWh in 2011 and reaching 3.2TWh in 2012. Elbas increases in importance as more wind generation enters the grid. The intra-day market functions as a discriminatory auction and the bids and offers are settled as soon as the offer meets demand.

4.2.1. Trade data

I analyze prices and volumes of settled trades that took place between the 1st of January 2010 and the 20th of October 2012.[64] The studied sample contains 404,744 trades. Most trades take place at hours 10 in the morning and 15 in the afternoon with accordingly 22 and 25 trades on average (Figure 1). During the night there are on average fewer trades, the market is less active as demand is relatively low and can be easily met by suppliers. There is a drop in the number of trades between hours 11 and 13 resulting in a two-hump shape of the hourly distribution of trades.

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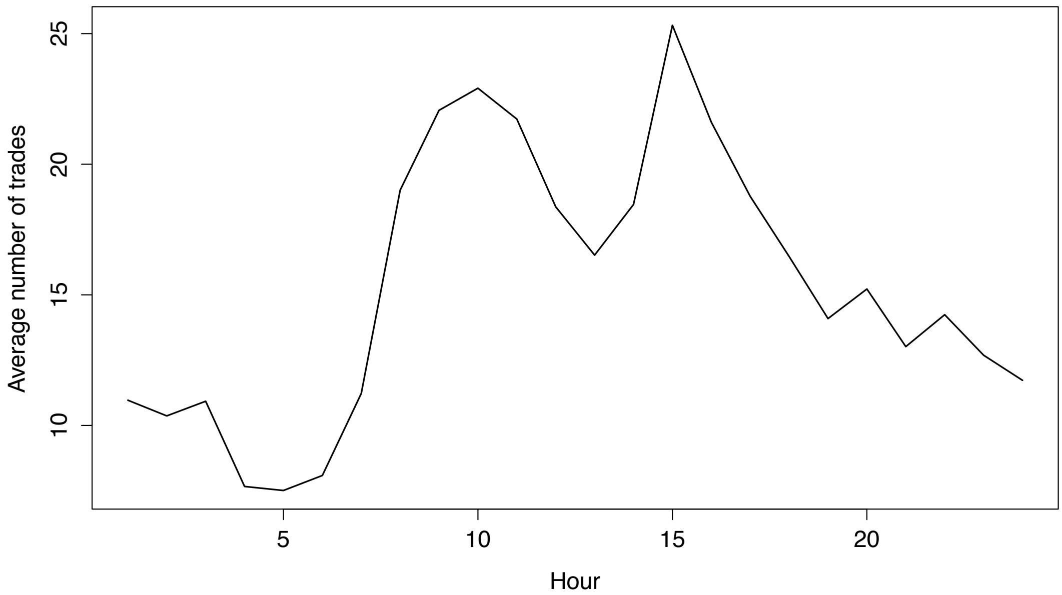
[63] http://www.nordpoolspot.com/Global/Download%20Center/Annual-report/annual-report_Nord-Pool-Spot_2012.pdf

[64] The identity of traders is not known either.

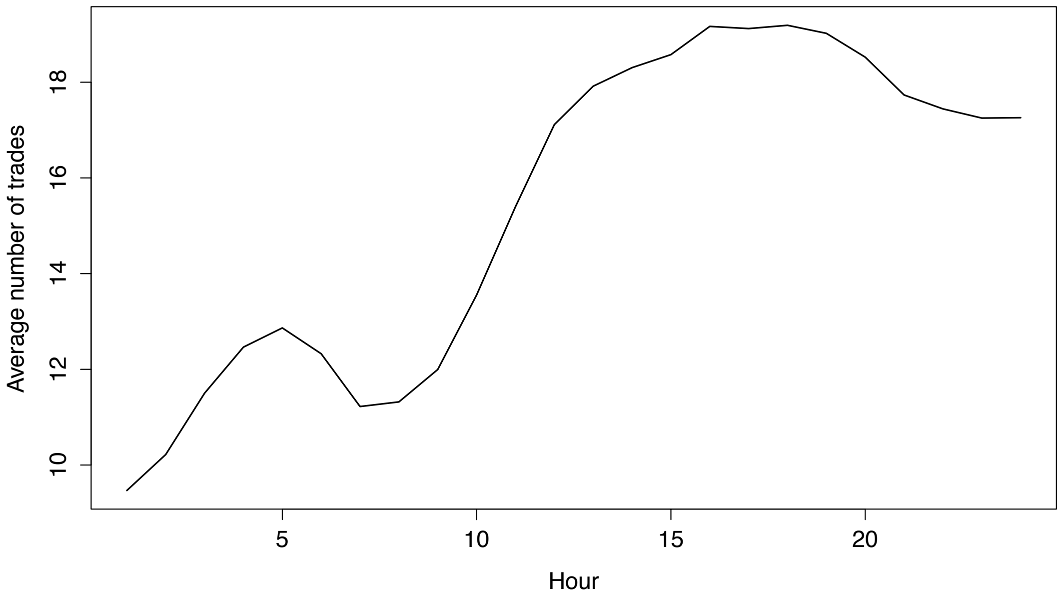
Figure 1. Average number of trades per hour



Note: This figure shows the average number of trades per hour.

While discussing the timing of particular trades it is important to note that the market in question is a continuous market and particular products (electricity that is to be delivered at a particular hour of the day) can be traded in different moments of the day. Therefore, a decrease in trading that is observed around noon does not necessarily correspond to the decrease in trades of the products to be delivered around noon. Figure 2 reports the average number of trades per product (there are 24 products every day). It shows that the number of contracts to be delivered later during the day increases. Contracts for delivery in the early morning hours (between hour 00:01 and 8:00) are not traded that often. Contracts for delivery later during the day are traded more frequently.

Figure 2. Average number of trades conditioned on the delivery time



Note: This figure shows the average number of trades according to the hour of contract's delivery.

4.2.2 Price

As the intra-day market operates as a discriminatory continuous auction, there is not one price for a product but a range of prices that can vary substantially. In the studied sample the range of prices obtained for the same product varied up to 951.5€/MWh (Table 1).

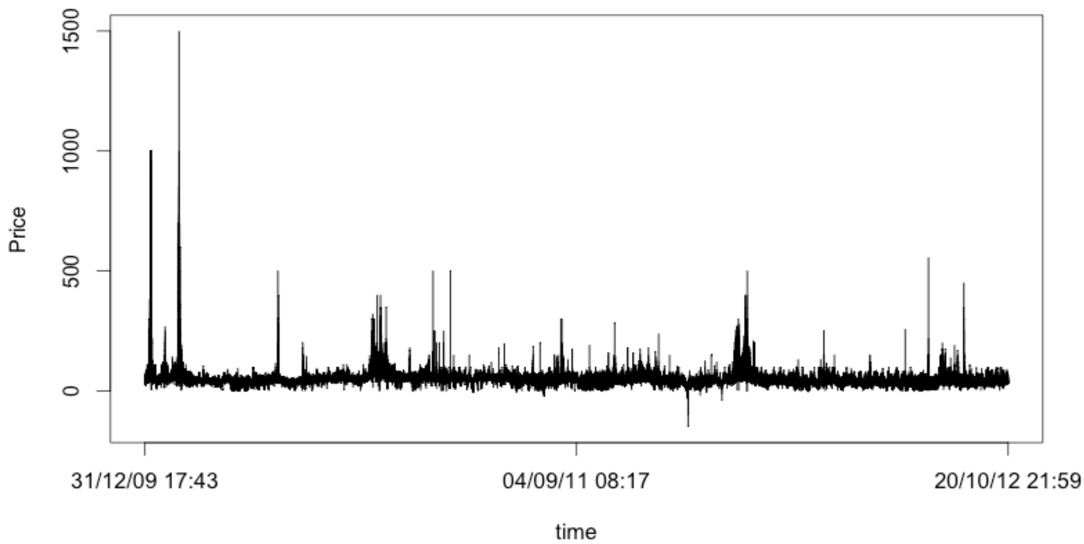
Table 1. Summary statistics describing the intra-day price

Variable	*Obs.*	*Mean*	*St dev.*	*Min*	*Max*
Price	404,744	47	27.09	-150	1,500
Diff	404,744	24.4	31.22	0	951.5

Note: This table presents summary statistics for the intra-day electricity price from the Nordic electricity market Nord Pool from the 1st of January 2010 to the 20th of October 2012. Diff stands for the difference between the lowest and the highest price for the same product. Price is reported in Euros per megawatt hour.

The mean price for the entire period was 47€/MWh, but there were instances with spikes (Figure 3). At the beginning of 2010 prices reached 1,500€/MWh and several spikes were registered throughout the studied period when prices reached around 500€/MWh. Interestingly there were moments when utilities were paying to sell electricity – the minimum price of -150€/MWh was reached in June 2011.

Figure 3. Evolution of electricity prices on the intra-day market



Note: This figure shows evolution of the intra-day electricity prices trade-by-trade on Nord Pool from the 1st of January 2010 until the 20th of October 2012.

4.2.3 Volume

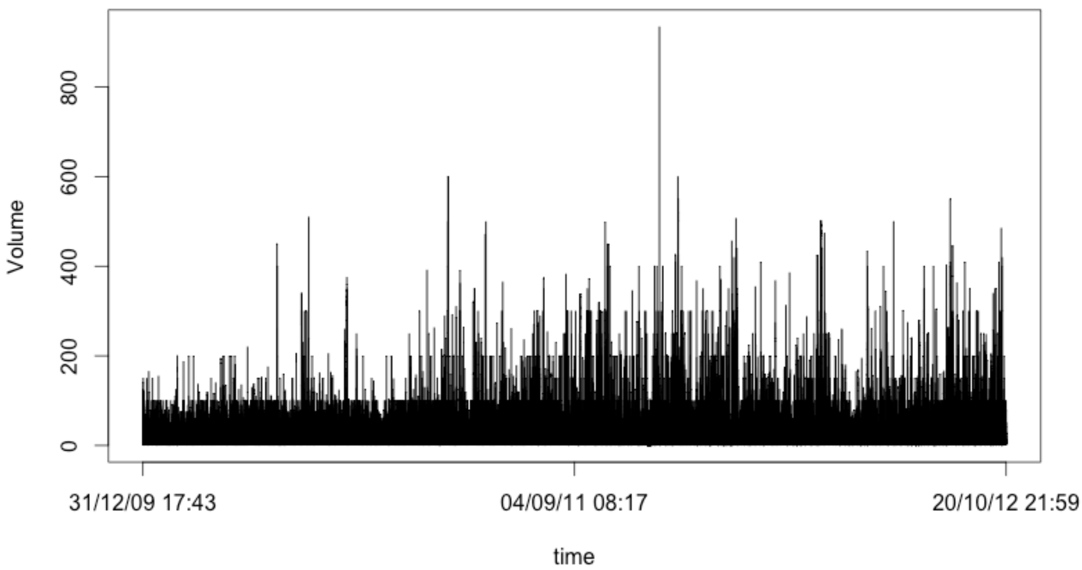
The size of traded contracts varies substantially from 1 kWh to 935 MWh. Summary statistics show that the mean size of volume traded in one trade was low and amounted to only 19.8 MWh (Table 2).

Table 2. Summary statistics describing volumes series

Variable	*Obs.*	*Mean*	*St dev.*	*Min*	*Max*	*Median*
Volume	404,744	19.78	26.3	0.001	935	10

Note: This table presents summary statistics for the volumes of traded electricity on the Scandinavian electricity market Nord Pool from the 1st of January 2010 to the 20th of October 2012. Volume is in MWh

Figure 4. Evolution of volume traded on the Nordic intra-day electricity market



Note: This figure shows evolution of the volumes transacted on the intra-day electricity market Nord Pool trade-by-trade from the 1st of January 2010 until the 20th of October 2012.

4.2.4 News data

The news dataset is composed of time-stamped announcements of changes to capacity reported by market participants. In Nord Pool market participants are obliged to publicly inform about any changes to generation, transmission and consumption of electricity that are larger than 100 MW and last for longer than 60 min. The news is released through Urgent Market Messages (UMMs) that are publicly available and bring information about the announced event. UMMs inform about the identity of the issuer, size of the outage and area affected by the event as well as other data. News messages are unscheduled and can be roughly divided into failure messages and news informing about future maintenance. Nord Pool rules dictate that a member experiencing a failure has to report it through UMMs within 60 min of the discovery of the problem. There are no clear rules regarding when maintenance announcements need to be made, except that is has to be sufficiently in advance. In the analyzed sample there were 2,702 novel failure messages, out of these 323 were due to transmission line failures (TSO) and 2,194 notifying about production failures.

For the purpose of this study I create a dataset describing each trade that took place between the 31/12/2009 17:00 and 20/10/2012 23:59. For each trade I report trade price, traded volume[65] and a dummy variable indicating whether there has been a novel UMM informing about failure within a specified time-frame around the trade time. I specify six UMM dummy variables:
UMM_5 indicating whether a UMM has been issued within 5 minutes after the trade;
UMM_10 indicating whether a UMM has been issued in the interval of 5 to 10 minutes after the trade;
UMM_15 indicating whether a UMM has been issued in the interval of 10 to 15 minutes after the trade;
UMM_-15 indicating whether a UMM has been issued within 15 min before the trade;
UMM_-30 indicating whether a UMM has been issued in the interval of 15 to 30 min before the trade;
UMM_-60 indicating whether a UMM has been issued in the interval of 30 to 60 min before the trade.

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[65] In high-frequency financial dataset there is often more detailed information available like: bid-ask spreads; in the dataset that I use this information does not exist.

In my dataset of 404,744 trades, 13,663 trades were done 5 min before a new UMM had been announced; 13,568 trades were done in the interval of 5 to 10 min before a new UMM had been announced; 12,789 in the interval of 10 to 15 min before a new UMM had been announced. 50,244 of all the trades had been concluded within 15 min after a new UMM had been announced; 49,408 trades took place in the interval of 15 to 30 min after a new announcement and 99,849 took place in the interval of 30 to 60 min after a news announcement.

Electricity producers may hold private information about their own generating units, however they will not have any private knowledge about potential problems on the transmission lines. I expect that if the private information is used, it is done so only with relation to the UMMs issued by electricity producers not with the messages announced by system operators. Therefore, in order to check for these effects, I create twelve new variables where time intervals around the news announcement are as specified above (*UMM_5* to *UMM_-60*) but distinguishing the identity of the issuer: electricity producer of system operator.

4.3. Information and public information releases

The classic reference for the discussions of market microstructure issues such as insider trading or market manipulation is Kyle (1985). The static version of the model analyses a stock market with three types of risk neutral traders: liquidity traders, a market maker who sets the price after observing the order flow and a single informed investor who trades with the aim of exploiting his private information. Both liquidity traders and the informed investor trade at the same time. The informed trader acts strategically, knowing that his demand will influence the price of the traded asset and his aim is to maximize his profit. The informed trader and liquidity traders submit their orders simultaneously; the market maker cannot distinguish among different orders and traders and observes only net order flow. He sets the execution price equal to his best estimate of the value of the stock given the observed order flow.

A similar model but in a dynamic version is analyzed by Admati and Pfleiderer (1988) who concentrate on the evaluation of the intra-day price and volume patterns. In their model the informational advantage of informed traders is only short-lived. Informed traders have a noisy version of the public information one period in advance. This assumption leads to the observation that they have no incentive to postpone their trading to future periods as their private information becomes public in the next period. Asymmetries in information distribution influence the adjustment of prices in the preannouncement periods, which continues upon news arrival. In case there is no additional news in the following periods, the volatility decreases.

A related model, which introduces long-lived information with decreasing value over time, had been developed by Foster and Viswanathan (1990). The informed trader receives information every day but some portion of this information becomes public each day making the information less valuable over time. The informed trader trades more aggressively as he is aware of the forthcoming public signal; hence more information is released through trading.

In these models asymmetric information explains price fluctuations in the periods around the announcement of public news. Traders with private information want to benefit from their superior knowledge about future events. As a result prices adjust to private information before the news is publicly announced. In case there is no informed trading in the preannouncement period, prices adjust to the new information after news arrival.

4.4. Modeling trading activity

In financial studies returns are usually calculated over a fixed time-window often 5 minutes (Bauwens et al. 2005) or 10 minutes (DeGennaro and Shrieves 1997). This approach is used when studying high-frequency markets. Trades on the Nordic electricity intra-day market are not that frequent, with at most 25 trades on average in the analyzed period. There are hours when there are no trades. This is why I analyze the data trade-by-trade instead of using returns over fixed intervals of time.

In order to distinguish between pre-announcement and post-announcement intervals, I divide the period around news announcements into three non-overlaping time intervals: a pre-response interval of 15 minutes before the announcement, a response interval which I define as within 15 minutes after the UMM announcement, and a post-response interval – 15 to 60 minutes after news announcement.

4.4.1. Estimation

Modeling of price time series is often done with the use of generalized autoregressive conditional heteroskedasticity (GARCH) models.[66, 67] The standard GARCH model has been described by Bollerslev (1986).

Using detailed trade information I estimate GARCH models with exogenous variables in the mean equation.[68] Private information is defined as public information in the periods before the announcement and is captured by the three variables: *UMM_5*, *UMM_10* and *UMM_15*. I specify the following model:

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{1}$$

$$y_t = \mu + \sum_{i=1}^{j} \vartheta_i r_{it} + \theta_1(y_{t-1} - \mu) + \theta_2\epsilon_{t-1} + \epsilon_t \tag{2}$$

$$\epsilon_t = \sigma_t z_t \quad \text{where} \quad z_t \sim N(0,1) \tag{3}$$

[66] I analyze the data trade by trade. However the data, although organized in time series are not spaced uniformly in time. Trades happen randomly, in some hours there are lots of trades, in others, especially off-peak trades are rare. I disregard the unregular spacing and assume that spacing of trades (time from on trade to another) is not informative for my analysis. One class of models that investigate informational content of the time elapsed in between trades is referred to as ACD (Autocorrelated Conditional Duration) models; however, the analysis of these models is not in the scope of this paper.

[67] Some examples of garch modeling of the impact of news/exogenous factors on the volatility of exchange rates can be found in: Degennaro and Shrieves (1997), Melvin and Yin (2000), Bauwens et al. (2005) or Goodhart et al. (1993)

[68] Models with exogenous variables in the time-varying conditional variance equation were excluded from the analysis on the basis of comparison of AIC criteria; moreover coefficients on these variables were not significant.

In the mean equation (2) I included j external variables r_{it}. I estimate the model (eq. 1-3) for GARCH (1,1)[69] first using price as the dependent variable and then I repeat the estimation for the traded volumes. Initially I use six external variables *UMM_5*, *UMM_10*, *UMM_15*, *UMM_-15*, *UMM_-30*, *UMM_-60*. Then, as the incentives can vary I divide the news announcements not only according to the announcement time relative to each trade but I also take into account the identity of the trader. I distinguish events reported by electricity producers from those announced by Transmission System Operators.

4.4.2. Properties of the series

Visual inspection of Figure 3 indicates that the series is stationary. To verify this statement I use Dickey-Fuller test. The results allow for rejecting the null hypothesis of a unit root (Table A2 in the Appendix). The LM test for autoregressive conditional heteroskedasticity rejects the hypothesis of no ARCH effects at 1% level (Table A1 in the Appendix).

The volume series is stationary and the LM test for ARCH effects allows rejecting the null of no effects (Tables A1 and A2 in the Appendix).

4.4.3. Seasonality

In the following section I transform the data in order to account for the expected level of price and volume for a trade in a particular product.

The data transformation consists of adjusting price and volume price series for the expected component associated with the traded product. The product-adjusted series are obtained by dividing prices and volumes by their expected components. These are calculated as average price and volume for a particular product over a month in a particular year. In this way the expected value captures the hourly, monthly and yearly seasonality for every trade.

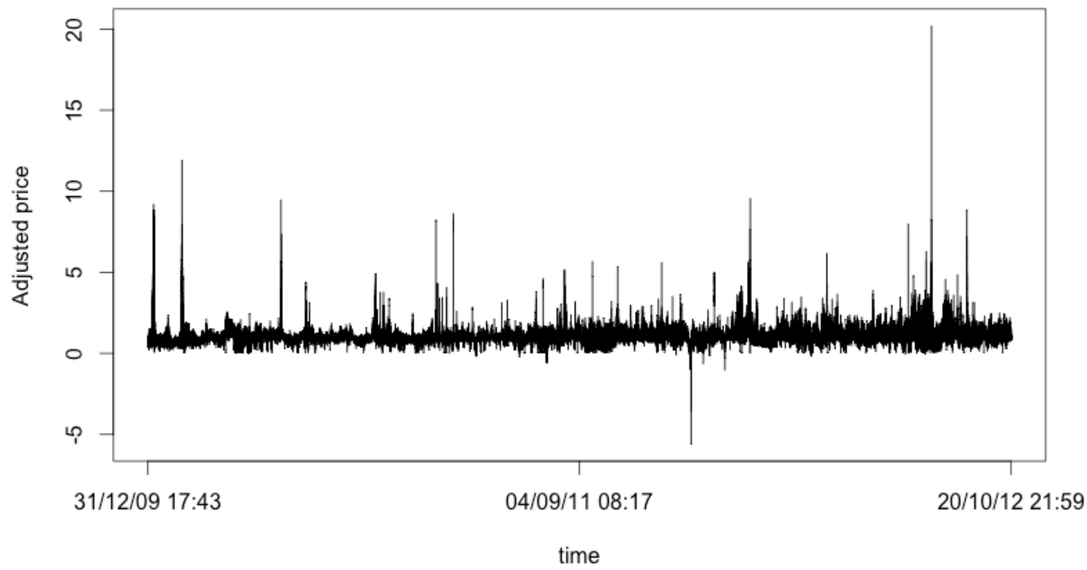
[69] Different models have been compared with the use of AIC criteria.

Table 3. Summary statistics describing adjusted price and volume series

Variable	*Obs.*	*Mean*	*St dev.*	*Min*	*Max*	*Median*
Adjusted price	404,744	1.0	0.345	-5.614	20.21	0.98
Adjusted volume	404,744	1.001	1.275	0.00006	38.46	0.58

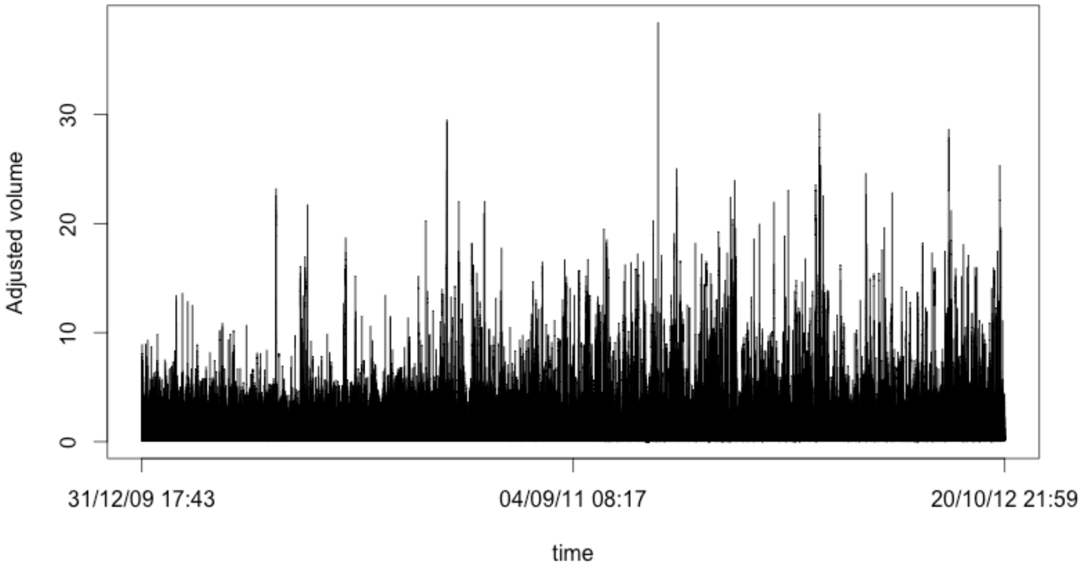
Note: This table presents summary statistics for the volumes of traded electricity on the Nordic electricity market Nord Pool from the 1st of January 2010 to the 20th of October 2012. Volume is in MWh.

Figure 5. Evolution of adjusted intra-day price



Note: This figure shows evolution of the product-adjusted Nord Pool intra-day electricity price trade-by-trade over the period from the 1st of January 2010 until the 20th of October 2012.

Figure 6. Evolution of product-adjusted volume traded on the intra-day electricity market



Note: This figure shows evolution of the product-adjusted volume traded on the Nord Pool intra-day market over the period from the 1st of January 2010 until the 20th of October 2012.

Both adjusted series are stationary and heteroscedastic (Appendix: Tables A1 and A2).

Adjusted series allow for capturing the unexpected element of every trade. The more original series deviate from the monthly product average the larger is the unexpected component.

4.5. Results

Estimation is done with R, using the rugarch package Ghalanos, A., (2014). Results of the estimation are reported in Table 4. Standard errors, which are reported in the table, are computed with White (1992) methodology, which provides asymptotically valid confidence intervals in samples with not normally distributed errors.

Table 4. Estimation results

Variable	*Price*	*Volume*	*Adjusted price*	*Adjusted volume*
Mu	48	19.01	0.999	0.96
	(2.31)***	(0.18)***	(0.01)***	(0.008)***
Ar1	1.39	1.19	1.38	1.17
	(0)***	(0)***	(0)***	(0.006)***
Ar2	-0.32	-0.12	-0.3	-0.12
	(0)***	(0)***	(0.003)***	(0.007)***
Ar3	-0.07	-0.05	-0.08	-0.05
	(0)***	(0)***	(0.002)***	(0.004)***
Ar4	-	-0.04	-	-0.03
	-	(0)***	-	(0.004)***
Ma1	-0.92	-0.93	-0.93	-0.91
	(0)***	(0.006)***	(0.004)***	(0.002)***
UMM_5	-0.1	-0.33	-0.003	-0.02
	(0.09)	(0.31)	(0.002)*	(0.01)
UMM_10	0.03	0.4	-0.001	0.02
	(0.11)	(0.41)	(0.003)	(0.02)
UMM_15	0.11	0.49	0.0002	0.02
	(0.11)	(0.46)	(0.005)	(0.02)
UMM_-15	0.1	-0.06	-0.001	-0.001
	(0.05)*	(0.19)	(0.002)	(0.009)
UMM_-30	0.01	-0.31	-0.001	-0.01
	(0.05)	(0.23)	(0.002)	(0.01)
UMM_-60	0.06	0.06	0.0001	0.004
	(0.04)	(0.16)	(0.002)	(0.007)
Omega	0.4	50.6	0.0001	0.14
	(0.02)***	(4.8)***	(0)***	(0.01)***
Alpha1	0.06	0.17	0.06	0.17
	(0)***	(0.01)***	(0.01)***	(0.01)***
Beta1	0.94	0.72	0.94	0.71
	(0)***	(0.02)***	(0.01)***	(0.02)***
AIC	6.7333	8.6378	-1.0578	2.6523

Note: This table shows results from the estimation of price and volume time series. Price series (columns 2 and 4) are estimated using ARMA (3,1) – GARCH (1,1). Volume series (columns 3 and 5) are estimated using ARMA(4,1) – GARCH (1,1). Robust standard errors are in brackets. Column 2 reports result from the estimation of the original price series. Column 3 reports results from the estimation of the original volume series. Columns 4 and 5 report results from estimation of the product-adjusted price and volume series. This adjustment captures the hourly, monthly and yearly seasonality.

An ARMA (3,1) – GARCH(1,1) model for price among specifications of price series works the best, though it is not completely successful. However, more complex models do not provide better results (as compared with Akaike Information Criterion, autocorrelation and partial autocorrelation plots) and the conclusions derived from news variables from those different models are similar.

Results show that there is no significant effect of price changes in the preannouncement period. Immediately before news arrival (5 minutes before UMM) a negative effect on prices is observed, but is not significant. A positive effect is identified in the contemporaneous interval, which is defined as the interval 15 minutes before a trade. The effect of news issued 45 minutes before a trade is still positive but smaller than in the first 15 minutes and is not significant. The results from the adjusted price series also suggest that the prices fall in the preannouncement period. This effect persists to 30 minutes after the news announcement but is not significant. The division according to the type of issuer brings some additional information (Table A3, Appendix). Non-significant effects are found in the preannouncement period. The price adjusts to the messages issued by system operators within 15 minutes after the announcement (result significant at the 11% level) and to the production failures in the interval of 30 to 60 minutes after the announcement. Results for the adjusted series do not deliver significant results for any of the announcements periods.

The best results for the volumes series have been obtained with the use of ARMA(4,1) – GARCH(1,1) specification, however, they were not completely successful either. Nevertheless, results for the news variables from different specifications, which were compared with the Akaike Information Criterion, autocorrelation and partial autocorrelation techniques, do not indicate any effect of news on the size of traded contracts.

4.6. Conclusions

The European Commission is introducing a set of new regulations on submission and publication of data in electricity markets (SPDEM)[70] accompanied by the rules on wholesale energy market integrity and transparency (REMIT).[71] These rules require public disclosure of detailed information concerning for example changes to transmission, generation or consumption that are larger than 100 MW and last for longer than "one market time unit" i.e. one hour for the Scandinavian electricity market (Nord Pool). In Scandinavia a similar system of information announcements has existed under the name of Urgent Market Messages (UMM) since 2004.

It is forbidden to use the information from UMMs before they are publicly disclosed. The purpose of this paper is to examine whether there are any patterns between news announcements and the levels and volatility of price and traded volumes. In this market there are market players who posses private information and this paper tries to answer the question whether they are using their information before it is made public.

With the use of a time series approach this paper investigates the behavior of prices and traded volumes in the period of 15 minutes prior to the announcement of a UMM and 60 minutes after UMM was issued. Results indicate that there is no effect of news on the volatility of prices or volumes. There is also no indication of news effects on the mean levels of prices or volumes in the preannouncement time intervals. The findings indicate that prices adjust in the period of first 15 minutes after the announcement of UMM.

Although channels informing about real-time changes to the situation on the power grid raise questions whether this increased transparency of markets is beneficial (von der Fehr 2013), they give the authorities and researchers a tool to check in a systematic way for the presence of trades based on private information.

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[70] EU, 2013

[71] EU, 2011b

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Appendix

Table A1. LM test for autoregerssive conditional heteroskedasticity (ARCH)

Series	*Chi-squared*	*p-value*
Price	236,409.3	p < 2.2e-16
Volume	146,955.9	p < 2.2e-16
Adjusted Price	141,049.3	p < 2.2e-16
Adjusted Volume	150,680.2	p < 2.2e-16

Note: H0: no ARCH effects vs. H1: ARCH(p) disturbance; Df=1

Table A2. Dickey-Fuller test for unit root

Series	*Test statistics*	*1% critical value*	*5% critical value*	*10% critical value*
Price	-181.769	-3.430	-2.860	-2.570
Volume	-345.198	-3.430	-2.860	-2.570
Adjusted price	-248.632	-3.430	-2.860	-2.570
Adjusted volume	-355.712	-3.430	-2.860	-2.570

Note: Number of obs. = 404743

Table A3. Estimation results

Variable	*Price*	*Volume*	*Adjusted price*	*Adjusted volume*
Mu	48	18.98	0.98	0.96
	(1.01)***	(0.17)***	(0.55)*	(0.008)***
Ar1	1.39	1.19	1.39	1.17
	(0)***	(0)***	(0.12)***	(0.006)***
Ar2	-0.32	-0.12	-0.32	-0.12
	(0)***	(0)***	(0.08)***	(0.007)***
Ar3	-0.07	-0.05	-0.07	-0.05
	(0)***	(0)***	(0.03)***	(0.004)***
Ar4	-	-0.04	-	-0.03
	-	(0)***	-	(0.004)***
Ma1	-0.92	-0.93	-0.93	-0.91
	(0.01)***	(0.006)***	(0.44)***	(0.002)***
Production_UMM_5	-0.04	0.02	0.003	0.0005
	(0.14)	(0.44)	(0.02)	(0.02)
Production_UMM_10	-0.02	0.42	-0.002	0.02
	(0.15)	(0.54)	(0.01)	(0.02)
Production_UMM_15	-0.02	0.75	-0.006	0.03
	(0.19)	(0.7)	(0.008)	(0.03)
Production_UMM-15	0.09	0.03	0.0004	0.004
	(0.07)	(0.28)	(0.02)	(0.01)
Production_UMM-30	0.04	-0.26	0.0007	-0.004
	(0.07)	(0.33)	(0.01)	(0.01)
Production_UMM-60	0.09	0.02	0.0004	0.003
	(0.05)*	(0.17)	(0.013)	(0.008)
TSO_UMM_5	-0.27	-0.7	-0.01	-0.04
	(0.19)	(0.46)	(0.009)	(0.02)
TSO_UMM_10	0.17	0.83	-0.005	0.03
	(0.18)	(0.69)	(0.008)	(0.03)
TSO_UMM_15	0.3	0.28	0.009	0.006
	(0.28)	(0.6)	(0.005)	(0.03)
TSO_UMM_-15	0.15	-0.31	-0.0004	-0.01
	(0.09)(*)	(0.29)	(0.03)	(0.01)
TSO_UMM_-30	-0.07	-0.3	-0.0009	-0.02
	(0.11)	(0.34)	(0.03)	(0.01)

TSO_UMM_-60	-0.03	0.17	-0.0009	-0.02
	(0.08)	(0.3)	(0.03)	(0.01)
Omega	0.4	49.79	0.0002	0.14
	(0.05)***	(4.8)***	(0.0001)*	(0.013)***
Alpha1	0.06	0.17	0.06	0.17
	(0)***	(0.01)***	(0.03)*	(0.01)***
Beta1	0.94	0.72	0.92	0.71
	(0)***	(0.02)***	(0.06)***	(0.02)***
AIC	6.7333	8.6378	-1.0540	2.6523

Note: This table shows results from the estimation of price and volume time series. Price series (columns 2 and 4) are estimated using ARMA (3,1) – GARCH (1,1). Volume series (columns 3 and 5) are estimated using ARMA(4,1) – GARCH (1,1). Robust standard errors are in brackets. Column 2 reports result from the estimation of the original price series. Column 3 reports results from the estimation of the original volume series. Columns 4 and 5 report results from estimation of the product-adjusted price and volume series. This adjustment captures the hourly, monthly and yearly seasonality. (*)$p<0.11$; *$p<0.1$; **$p<0.05$; ***$p<0.01$

Essays on Electricity Markets

This thesis consists of four essays examining the functioning of electricity markets. The first article builds on a game-theoretical model, the three other articles discuss empirically the link between information and price formation process.

Comparison of congestion management techniques: Nodal, zonal and discriminatory pricing, compares different market designs used to handle congestion in electricity transmission networks.

Market-specific news and its impact on forward premia on electricity markets is an empirical analysis of the impact messages informing about sudden events affecting the power market have on price differences between the day-ahead and the intra-day Nordic electricity market.

Strategic withholding through production failures, studies a previously unexamined way through which electricity producers can withhold capacity in order to increase prices on the Nordic electricity market and verifies whether the decision to stop production and inform about a sudden failure is based on economic incentives or rather is a result of a technical problem.

Private and public information on the Nordic intra-day electricity market is an investigation of how traders on the Nordic intra-day electricity market react to public news about sudden failures on the power grid and whether they use private information about forthcoming outages in trading.

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ISBN 978-91-7258-927-8

Doctoral Dissertation
in Economics
Stockholm School of Economics
Sweden, 2014