Essays on market design and strategic behaviour in short-term power markets

Inauguraldissertation
zur
Erlangung des Doktorgrades
der
Wirtschafts- und Sozialwissenschaftlichen Fakultät
der
Universität zu Köln

2019

vorgelegt
von

Diplom-Wirtschaftsingenieur Johannes Viehmann

aus

München

Referent:	Prof. Dr. Marc Oliver Bettzüge
Korreferent:	Prof. Dr. Felix Höffler
Tag der Promotion:	15.03.2019

Acknowledgements

First of all I would like to thank my supervisor Prof. Dr. Marc Oliver Bettzüge who not only gave me the chance to be an external doctoral candidate, but also inspired me to further improve and who provided guidance ever since I began working on my thesis in September 2008. Equally, I would like thank Prof. Dr. Felix Höffler for co-referring my thesis and constantly providing feedback and sound academic advice.

I would also like to thank my co-authors Jan Richter, Stefan Lorenczik and Raimund Malischek. Jan's contribution and mathematical skills were essential in our common paper *The value of information in explicit cross-border capacity auction regimes in electricity markets.* Equally, I thank Stefan and Raimund for being co-authors in our common paper *Multi-unit multiple bid auctions in balancing markets: an agent-based Q-learning approach.*

A special thanks goes to Egbert Laege who enabled me to be a doctoral candidate next to my regular job as a power trader. Also, thank you to all EWI colleagues - in particular in alphabetical order to Christina Elberg, Caroline Löffler (maiden name: Dieckhöner), Marco Nicolosi, Jochen Schwill and Hendrik Sämisch - for helpful comments and suggestions and for creating an inspiring environment. Moreover, I would like to thank Oliver Grothe, Thomas Niedrig and Frowin Schulz for helpful comments and Broghan Helgeson, Edward Morrison and my wife Sugiha Densink-Viehmann for carefully proofreading my and our common papers for grammatical errors. For administrative support, I would like to thank in alphabetical order Daniel Balistrieri, Monica Deckers, Martina Mundorf, Christel Schäfer, Monika Schmid and Daniel Verdu.

Finally, I would like to thank my brother Manuel, my mother Christine, my father Reiner and my dear friends for their support.

Johannes Viehmann October 2018

Contents

List of Abbreviations

ACER Agency for the Cooperation of Energy Regulators

API Application Programming Interface

AS Ancillary Services

ATC Available Transfer Capacities

BNetzA Bundesnetzagentur for Electricity, Gas, Telecommunications, Post and Railway

BRP Balancing Responsible Party

BSP Balancing Service Provider

CACM guideline on Capacity Allocation and Congestion Management

CAO Central Allocation Office

CASC Capacity Allocating Service Company

CRn Concentration Ratios of the n suppliers with the highest market shares

CWE Central Western European Market Coupling

DA Day-Ahead

DPA Discriminatory Price Auction (same as PABA)

EEG German Renewable Energy Act

EEX European Energy Exchange

ENTSO-E European Network of Transmission System Operators for Electricity

EPEX European Power Exchange (formerly known as EEX)

EUPHEMIA Pan-European Hybrid Electricity Market Integration Algorithm

EXAA Austrian Power Exchange

FBA Frequent Batch Auction

FBMC Flow-Based Market Coupling

FCFS first-come, first-serve

GCC Grid Control Cooperation

HHI Herfindahl-Hirschman-Index

IGCC International Grid Control Cooperation

MR Minute Reserve

MUMB Multi-Unit Multiple Bid

NCEB Network Code on Electricity Balancing

OTC Over-The-Counter

OTR Order-to-Trade Ratio

PABA Pay-as-Bid Auction (same as DPA)

PCR Price Coupling of Regions

PJM Pennsylvania-Jersey-Maryland

PR Primary Reserve

PSI Pivotal Supply Index

PX Power Exchange

SR Secondary Reserve

TSO Transmission System Operator

UPA Uniform Price Auction

VoLL Value of Lost Load

XBID Cross-border Intraday Market Project

Introduction

Within the last 10 years, I have compiled the doctoral thesis at hand next to my regular job as a short-term power trader at a major German utility. Therefore, the motivations of all 4 essays presented here originate from “real-world” problems and subjects which I have experienced during my professional career. It is amazing at which speed problems can be solved and new problems can be created in this highly dynamic industry. Generally, short term markets are much more efficient than 10 or 15 years ago, but unilateral national actions remain a large obstacle for complete European harmonisation. Even though national and European regulatory authorities regularly invite for public consultations with regard to market design changes, the sheer number of stakeholders involved with diverging interests – such as pure traders, producers, consumers, power exchanges, transmissions system operators and others – often results in a very complex decision making process. Frequently, it is not transparent who takes the final decision and on which facts the decision is based on. Also, some decisions are later revised as the reaction and behaviour of market participants was not anticipated correctly. This thesis first attempts to order the main subjects in German and European short-term power markets in chapter 1. In the three subsequent essays, I deal with very specific aspects of market design and strategic behavior in the hope that my, and the common work with my co-authors will contribute to more fact based decision-making and less trial and error in the future. Even though there is a clear idea behind the structure of this thesis, all essays/chapters stand for their own and may be read in any order.

My first essay *State of the German short-term power market*, based on Viehmann (2017)[1], is an extensive meta study that covers the main short-term power markets with focus on trading, efficiency and market design issues and serves as introduction to, and motivation for the subsequent chapters. The five short-term markets considered are the Day-Ahead (DA)-market, cross-border trading and redispatch, intraday trading, Ancillary Services (AS) and the balancing energy market. I find that the DA-market is certainly the most mature and efficient short-term power market, particularly since Price Coupling of Regions (PCR) and smart block bidding were introduced. Also, fears

[1] Available here: https://doi.org/10.1007/s12398-017-0196-9.

that Over-The-Counter (OTC)-trading might be non-transparent and inefficient which was part of the motivation of, and rejected in my second paper (see chapter 2) have been overcome in the meanwhile. The introduction of implicit DA cross-border auctions, PCR and Flow-Based Market Coupling (FBMC) also improved efficiency at the borders considerably. However, there is still a significant number of explicit cross-border auctions, whose inefficiencies we explore in chapter 3. With regard to intraday markets, AS and balancing energy, there is some potential for market design improvements and European harmonisation. We find two trends that give cause for concern. One being that regulators in AS-markets focus mainly on consumer surplus (low prices) and neglect social welfare by introducing price caps, reducing transparency and opting for Discriminatory Price Auctions (DPAs), an issue extensively covered in chapter 4. This trend should be reversed as markets mature and market power of incumbent generators vanishes. Secondly, non-marked based redispatch measures and other interventions by Transmission System Operators (TSOs) such as curtailment of renewable generation due to grid constraints have increased significantly in recent years.

In my second paper *Risk Premiums in the German Day-Ahead Electricity Market*, based on Viehmann (2011)[2], I conduct an empirical analysis of risk premiums in the German DA electricity wholesale market. The foundation of this work was laid by two much-noticed publications by Bessembinder and Lemmon (2002) and Longstaff and Wang (2004). The former analytically show how risk premiums depend on the skewness in the spot power price distribution and the latter conduct an empirical analysis on risk premiums in the Pennsylvania-Jersey-Maryland (PJM)-market. Using a similar approach, I compare hourly price data of the European Energy Exchange (EEX)-auction and of the OTC-market which takes place prior to the EEX-auction. To my knowledge, I was the first to use data provided by the Austrian Power Exchange (EXAA) as a snapshot of the OTC-market two hours prior to the EEX-auction. Ex post analysis found market participants are willing to pay both significant positive and negative premiums for hourly contracts. The largest positive premiums were paid for high demand evening peak hours on weekdays during winter months. By contrast, night hours on weekends featuring lowest demand levels display negative premiums. Additionally, ex ante analysis found a strong positive correlation between the expected tightness of the system and positive premiums. For this purpose, a tightness factor has been introduced that includes expectations of fundamental factors such as power plant availability, wind power production and demand. Hence, I can support findings by the two publications above that power traders in the liberalised German market behave like risk-averse rational economic agents. Additionally, I would like to mention that I have recently learned that Valitov (2018) has reproduced my essay and has computed higher significance levels

[2] Available here: https://doi.org/10.1016/j.enpol.2010.10.016.

for the risk premiums in table 2.3, while the absolute size of the risk premiums was replicated. According to Valitov (2018), this difference might be due to a different lag structure of the respective Newey-West standard errors. As these findings are not inconsistent with, and only strengthen the conclusions that I have drawn, I have decided to leave the original version of my essay as published in Viehmann (2011) in this thesis.

In the third paper *The Value of Information in Explicit Cross-Border Capacity Auction Regimes in Electricity Markets*, which is joined work with my co-author Jan Richter and based on Richter and Viehmann (2014)[3], we analyse the strategic behavior of firms endowed with transmission rights that arises when transmission capacity between electricity markets is explicitly auctioned. We identify three forces regarding capacity auctions that diminish social welfare: First, firms play a Cournot game, which prevents an efficient market outcome. Second, the presence of capacity constraints further reduces social welfare. Third, incomplete information reduces welfare as well, as in the presence of incomplete information, firms exercise their transmission rights less aggressively. By comparing the equilibria for the three information regimes, we find that revealing information to firms increases social welfare. Even though most DA cross-border capacities are awarded by the means of implicit auctions in the meanwhile, there is a significant number of explicit auctions in Europe to the present day. As long as explicit auction regimes are still in place, we recommend that auction offices provide as much information as possible about the first stage results in order to maximise social welfare.

The fourth paper *Multi-unit multiple bid auctions in balancing markets: an agent-based Q-learning approach* is joined work with my co-authors Stefan Lorenczik and Raimund Malischek, was finalised end of 2018 and is currently in the process of publication. We compare the two common auction types Uniform Price Auction (UPA) and Discriminatory Price Auction (DPA). Both market schemes cannot be thoroughly analytically analysed due to the complex strategy space in repeated Multi-Unit Multiple Bid (MUMB)-auctions. A first idea to approach this issue by the means of a laboratory experiment was rejected and modified towards and agent-based approach. Hence, we develop and apply an agent-based Q-learning model to simulate strategic bidding behaviour. We compare the performance of both auction types under a variety of market conditions and information regimes. We observe that UPAs lead to higher prices for all market set-ups. This is mainly due to the fact that players aggressively engage in bid shading by rising the price of their second bids as described by Krishna (2002). Even with low bid acceptance rates, their first bid can profit disproportionately from an elevated second bid. This is not the case in DPAs. Even though we find that UPAs generally feature higher efficiencies, we show several examples in which the efficiency of UPAs is worse than in DPAs. This is particularly true for low demand to supply ratios

[3] Available here: https://doi.org/10.1016/j.enpol.2014.03.023.

and for certain cost allocations among the players. Finally, we are able to analyse the influence of published information concerning previous auctions on average prices. For this purpose we introduce demand uncertainty in our model. Although the effect of providing more information about the demand level of previous auctions is ambiguous with symmetric players, prices tend to increase with asymmetric players with additional information. This is due to the fact the large player aggressively differentiates its bidding strategy with respect to the sub demand levels as he knows whether he is pivotal or not. Without additional information, the large player bids at lower prices as he has to guess its strategic position.

State of the German short-term power market

This chapter is based on Viehmann (2017)[4].

Abstract

The paper at hand provides a comprehensive overview of the current state of the German short-term power market with focus on trading, efficiency and market design issues. The overview covers five main short-term power markets, Day-Ahead trading and Power Exchanges, as well as Cross-border trading and Redispatch, Intraday trading, Ancillary Services and finally the Balancing energy market.

[4]Available here: https://doi.org/10.1007/s12398-017-0196-9.

1.1 Introduction

The paper at hand provides a comprehensive overview of the current state of the German short-term power market with focus on trading and efficiency. The pivotal question is whether current market designs are appropriate to maximise social welfare. If this can't be confirmed, trade-offs between technical restrictions, transparency requirements, the structure of the supply side and regulators focusing mainly on consumer surplus are analysed, which prevent markets from being fully efficient. The emphasis is on Germany due to it's central location in Europe, it's sheer size and the rapid increase of renewable generation in recent years. This development forced the German power market into a state of transition. As a result, developments in Germany might serve as a blueprint for other European countries. The introduction of negative day-ahead prices, the implementation of a very liquid intraday trading, a quarter hourly auction and market-based systems for the procurement of *Ancillary Services (AS)* are just some examples of Germany's pioneering role. On the other hand, negative effects of the rapid changes such as the excessive use of non-market based redispatch measures and system endangering imbalance price regimes shall also be explored. As a matter of course, cross-references to other European countries and harmonisation projects are included as the German market is well interconnected with neighbouring markets.

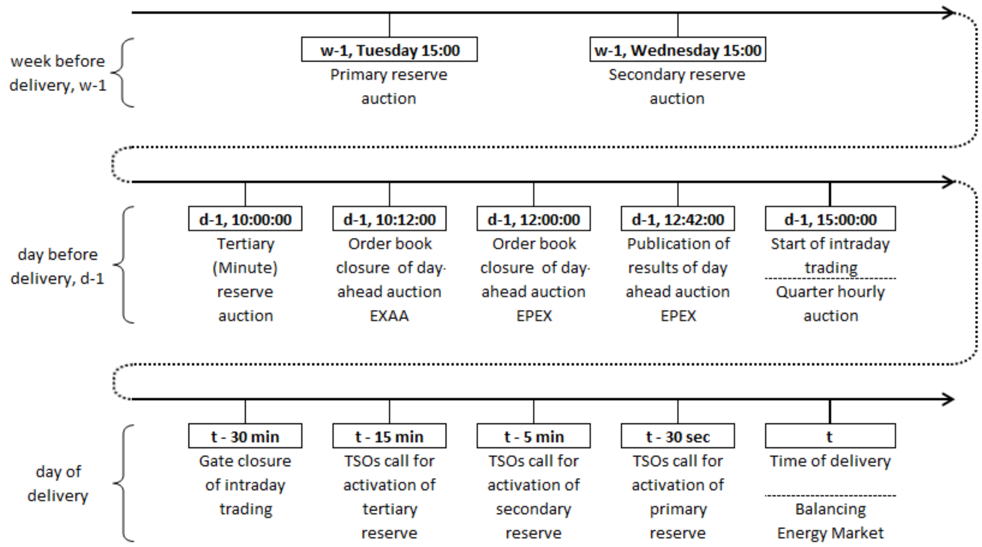


FIGURE 1.1: Timeline of short-term power trading in Germany

Five main short-term power markets have been identified and will be covered in this article along their operational timeline as shown in figure 1.1. Section 1.2 presents the *Day-Ahead (DA)* market and *Power Exchanges (PXs)* at which a large bulk of production and consumption planning is traded. The exchange of power between (cross-border trading) and within (redispatch) market areas is introduced in Section 1.3. Section 1.4 covers intraday trading activities which span from DA to gate closure shortly before start of delivery. In parallel to these energy only markets, *Transmission System Operators (TSOs)* procure balancing capacities week-ahead or DA and call for the activation of balancing energy shortly before time of delivery as shown in Section 1.5 dealing with Ancillary Services. Section 1.6 focuses on real-time system balancing and Section 1.7 concludes.

1.2 Day-Ahead trading and power exchanges

In DA markets, the lead time to actual delivery is sufficiently short to plan and trade production and consumption schedules. Typically, the majority of participants is active, liquidity is high and DA-prices serve as a reference for both, preceding forward and future markets as well as subsequent intraday markets.

1.2.1 Over-the-counter versus exchange based trading

The two market places of German power DA-trading are the continuous *Over-The-Counter (OTC)*-market and the PXs *Austrian Power Exchange (EXAA)* and the *European Power Exchange (EPEX)*[5]. Due to its very high liquidity EPEX[6] is widely regarded as the reference point for German power prices. Both market places, OTC and exchange based trading can be used interchangeably (Rademaekers et al., 2008). However, some important differences shall be mentioned. While OTC contracts are continuously traded mainly prior to the closure of EPEX books at noon, the PX holds a sealed-bid auction. Also, OTC-broker fees are significantly lower than trading fees at PXs, but firms face a counterparty credit risk[7]. While OTC-traded DA volumes were rather unchanged in recent years according to a survey of market participants, exchange-based trading volumes continued to increase. EPEX DA traded volumes more than doubled in 2015 compared to 2007[8]. This is mainly due to the fact that renewable generation units under the *German Renewable Energy Act (EEG)* are incentivised to sell their production at EPEX.

[5] formerly known as *EEX*.

[6] even though EPEX is active in other market areas such as France and Switzerland, we will only refer to EPEX in terms of the German market area hereafter.

[7] a more detailed comparison of OTC and exchanged-based DA trading at the German power market can be found in Viehmann (2011).

[8] according to press releases published by EPEX Spot, traded volumes increased from 127 TWh in 2007 to 264 TWh in 2015.

Before EU regulation No 1227/2011 on wholesale energy market integrity and transparency (REMIT) went into force in late 2011, EU policymakers and regulators were suspicious of OTC-trading as it was considered to be intransparent[9]. Among other measures, this regulation imposes strict rules on data collection and reporting of all (OTC)-trades conducted[10]. To the author's knowledge, there has been no evidence of systematic mispricing of OTC versus exchange-based contracts in the German power market. The energy sector inquiry by the European Commission (2007) found that prices of the German OTC-DA market and PX-prices were very closely correlated both in terms of development and levels. This seems to be plausible as continuous arbitrage in a functioning market would rule out different prices for identical contracts at competing market places.

However, perfect continuous arbitrage is not possible as the continuous OTC-market trades prior to the EPEX book closure and is considered to be the last forward market prior to the final auction. A more detailed analysis of this subject was published by Viehmann (2011). He compared EPEX and EXAA prices, while EXAA price data is considered to provide a snapshot of the continuous OTC-market two hours prior to the EPEX auction. While on average, prices were very similar (for the years 2005 to 2008), positive risk premiums were found for tight peak hours and negative premiums for offpeak hours with lowest demand. As predicted by Bessembinder and Lemmon (2002) premiums could be directly linked to the expected skewness of power prices. Hence, Viehmann (2011) confirmed that power traders in liberalised markets behave like risk-averse rational economic agents. They are willing to pay premiums if there is a risk of price spikes in order to avoid large losses that might incur to those who hold short positions in the forward market. Following the logic above, it is not surprising that Ziel et al. (2015) discover that EPEX price forecast models improve significantly if EXAA prices are included.

1.2.2 Exchange market design

The basic market design of EPEX is widely accepted and unlikely to be changed in the near future. Every day at 12:00 p.m., EPEX closes its order books and conducts a sealed-bid *Uniform Price Auction (UPA)* for the 24 hours of the next day. It is a combinatorial auction as the 24 individual hourly products can be linked via block orders containing two or more hours (see Meeus et al. (2009)). Additionally, the German market area[11]

[9] even if OTC-trading if often facilitated by electronic broker platforms, it takes place directly between two counterparties. A common database of these trades did not exist.

[10] see also regulation (EU) No 1348/2014 on data reporting implementing § 8(2) and § 8(6) of Regulation (EU) No 1227/2011 of the European Parliament and of the Council on wholesale energy market integrity and transparency.

[11] the term market area is also often referred to as market zone or bidding zone.

is linked to neighboring market areas via cross-border capacities, which are implicitly auctioned off by the *Price Coupling of Regions (PCR)*-algorithm and hence affect the order books in the German market area as well[12].

The most recent systematic discussion of auction rules at the German PX was published by Grimm et al. (2008). They favour UPAs over *Pay-as-Bid Auctions (PABAs)* as the later ones are more prone to inefficient market outcomes[13]. Furthermore, Grimm et al. (2008) support the existence of price caps at PXs in general in order to avoid the abuse of market power in highly concentrated markets. However, they argue as well that with perfect competition, price caps should not be below the *Value of Lost Load (VoLL)*. The price cap at the DA-EPEX auction is set to 3,000 €/MWh. This value seems to be reasonable as it has never been reached on the one side and it is at the lower end of the range of what e.g. Cramton and Stoft (2008) consider to be the VoLL on the other side. More controversial is the determination of the price floor. In September 2008, EPEX was the first PX in Europe that reduced the price floor from 0 €/MWh to negative prices (-3,000 €/MWh)[14]. The introduction of negative prices was necessary in order to avoid pro-rata allocation at prices of 0 €/MWh and the resulting loss in social welfare (Viehmann and Sämisch, 2009). Negative prices mainly occur in hours with low load levels, high infeed of renewable energies and conventional production units that feature short-term negative marginal costs due to technical restrictions (Nicolosi, 2010). Furthermore, Viehmann and Sämisch (2009) illustrate that the generation of renewable production units with marginal costs of 0 €/MWh at negative prices produces a deadweight loss. Nevertheless, renewable generation is incentivised by the EEG to produce even at negative prices with one exception. According to § 24 of the latest EEG amendment, large wind production units put in operation after the year 2015 are now incentivised not to produce if prices are negative for six or more consecutive hours.

The latest EPEX innovation was the introduction of a quarter hourly DA auction[15] in December 2014. Order books close at 3 p.m.[16] and the same algorithm is used as for the hourly DA auction, but block bids are not permitted and cross-border capacities are not taken into account. TSOs were pushing for this additional auction in order to avoid imbalances (see Section 1.6) by enabling market participants to trade intra-hour variations of their production and consumption profiles already in DA. Knaut and Paschmann (2017) show that the high price volatility of the quarter hourly market (compared to the

[12]cross-border capacities to some neighboring market areas are still auctioned-off by the means of explicit cross-border capacity auctions, see Section 1.3.1 for more details.

[13]see Section 1.5.1 for a more in depth discussion of UPAs vs. PABAs.

[14]with the implementation of PCR in February 2014, price floor was increased to -500 €/MWh.

[15]Officially named 15-min. intraday auction as it is held after the DA nomination deadline at 2.30 p.m.

[16]in contrast to EPEX, EXAA holds a combined auction of hourly and quarter hourly products to ensure that the average of four quarter hourly prices are equal to the hourly price.

hourly price index) and resulting inefficiencies are likely due to restricted participation of producers and missing cross-border trades.

1.2.3 Operational efficiency

The operational efficiency of PXs often is neglected in the academic world. However, it is of utmost importance when it comes to minimising overall system cost and maximising total welfare. The complexity of physical constraints of especially thermal production units pose a difficult challenge to producers and PXs. EPEX like most other European PXs[17] allows for so-called block orders that facilitate the consideration of start-up costs, minimum operating times, minimum downtimes, ramping rates and other constraints. Unlike hourly orders that can be executed partially, block orders can only be executed all-or-nothing. As block orders are a combination of hourly orders, the exchange algorithm has to solve a nonlinear problem. In order to reduce computational complexity, PXs like EPEX restrict the maximum size, the type and/or the number of block bids which in return might lead to suboptimal market outcomes. Some of these restrictions are discussed by Meeus et al. (2009). EPEX has gradually increased the maximum block size for the German market area in recent years. In October 2010, maximum block size was increased from 250 MW to 300 MW. In December 2011 and December 2015, it was further raised to 400 MW and 600 MW respectively. In January 2017, EPEX increased the maximum block size to 800 MW.

With the implementation of the PCR-initiative in February 2014 (see also Section 1.3) a new *Pan-European Hybrid Electricity Market Integration Algorithm (EUPHEMIA)* was introduced which allows for so called smart block bid orders such as linked and exclusive block bids. With linked block orders, the acceptance of a (child)-block can be made dependent on the acceptance of another (parent)-block. With exclusive block orders, market participants can offer a particular production unit across different time frames and/or operation modes. EUPHEMIA accepts at maximum one block which maximises overall social welfare. Detailed information on the smart block bid types can be found in the public EUPHEMIA description by EPEX Spot et al. (2016). Smart block bids in general reduce the problem of mutual exclusive standard block bids and significantly improve the possibility of placing (ex-post) optimal block orders. In January 2017, EPEX eased restrictions on the usage of smart block bids due to computational complexity[18].

[17] The only exception is the Italian power exchange IPEX.

[18] currently, EPEX permits three linked block bid families per portfolio and a maximum of seven block bids per family. Additionally, EPEX allows for five exclusive block bid families per portfolio with a maximum of 24 block bids per family.

A reduction of existing restrictions with regard to the maximum size and number of (smart) block bids is necessary to further improve operational efficiency in the future. Additionally, one could think of the introduction of new order types such as complex orders and flexible hourly orders, which are already implemented in EUPHEMIA (EPEX Spot et al., 2016) but not in use for the German market area. Furthermore, a combination of exclusive and linked block orders would help to improve the optimisation of daily pump-storage units[19]. A further development of complex orders are thermal orders (Van Vyve, 2011), which are already in use in US pool-based power systems. With thermal orders market participants send all technical parameters and cost specifications of a thermal unit to the PX, which in turn calculates the optimal operation mode of that unit. However, as the introduction of thermal orders would be a significant step from a self-dispatched to a central-dispatched power system, it is likely to encounter severe resistance. The same holds true for the idea to improve social welfare by reducing paradoxically rejected block bids (see Meeus et al. (2009)) via uplifts or side payments (see Van Vyve (2011), Madania and Van Vyve (2015) and Grimm et al. (2008) for more details). Uplifts or side payments are considered to be a deviation from a single uniform price (per market area) and hence currently politically not desired in Europe.

1.2.4 Market structure and market power

There is a long debate on the degree of market concentration and abuse of market power in the German electricity market[20]. Müsgens (2006) compared actual German power prices to those generated by a fundamental dispatch model. He observed that market prices were very close to marginal production costs for the first months under investigation (mid 2000 to mid 2001), but then increased to on average 50 percent - and even 75 percent in peak times - above marginal cost for the subsequent period (mid 2001 to mid 2003). He names increasing market concentration through mergers during that time-frame as one plausible explanation. A study prepared by London Economics (2007) for the European Commission and Weigt and Hirschhausen (2008) obtain similar results for the years 2003 to 2005 and 2006 respectively. However, several authors questioned these reports as they considered the data used to be incomplete (see e.g. Ockenfels (2007) and Weber and Vogel (2007)) and questioned how producers would recover fixed costs. A sector inquiry observed a high degree of market concentration within the German market for the years 2007 to 2009, but did not find evidence of capacity withholding or market abuse (Bundeskartellamt, 2011). Using a conjectural

[19] see Muche (2014) on the complexity of DA pump-storage unit bidding.

[20] the abuse of market power in electricity markets usually increases producers surplus and decreases consumer rents. As long as demand is inelastic and the least-cost production units are employed, total welfare is not affected.

variations and fundamental market model approach, Graf and Wozabal (2013) could not find any evidence of systematic abuse of market power and concluded that the market was competitive for the years 2007 to 2010.

To sum up, while some studies find prices above marginal costs in the first decade of this century (for the years 2001 to 2006), there is no evidence of market abuse in recent years. This might be due to increased transparency in the market, but also due to a change in market structure and market shares. The EU directive 2005/89/EC and the corresponding national implementation Kraftwerks-Netzanschlussverordnung (KraftNAV) ensured non-discriminatory access to high-voltage transmission grids and aimed at promoting new generation capacity and the entry of new production companies to the market. While the four largest generators (RWE, E.ON, Vattenfall, ENBW) produced 406.8 TWh[21] in 2007 (Bundeskartellamt, 2011), their production declined by more than 26% to 299.4 TWh[22] in 2014 (BNetzA, 2015). According to the same reports, production from renewables (promoted by the EEG) more than doubled from 67.0 TWh in 2007 to 154.8 TWh in 2014. The rise of renewable production by itself is a very strong argument against any kind of market abuse as production units operating under the EEG reduce the market share of incumbent generators and have no incentive to withhold capacity or to bid strategically. Merely at times with little or no renewable generation, conventional producers might potentially exercise market power (Milstein and Tishler, 2015).

The total number of market participants is increasing steadily, today more than 200 companies are registered to trade at EPEX. Next to the fundamental changes on the producers side, the structure of financial players, which are important to provide liquidity and exploit arbitrage opportunities, changed as well. Most investment banks such as Barclays, Deutsche Bank, JP Morgan or BoA Merril Lynch have either closed down or significantly reduced their European Gas and Power trading activities due to increased regulatory pressure during the last three years. At the same time, smaller energy traders such as NEAS or Next Kraftwerke, hedge funds such as Cumulus Energy or Citadel and commodity merchants such as Vitol and Mercuria, which all face less regulatory pressure than investment banks increased their activities.

Due to the success of PXs in DA markets and the fact that several mergers lead to a rather monopolistic PX structure in Germany but also in most other European countries, Meeus (2011b) is discussing how regulation can ensure that market power of PXs does not endanger European market integration. He proposes enhanced transparency requirements, introduction of governance rules and the continuation of explicit long-term cross-border capacity auctions to mitigate market power of PXs. The implementation

[21] equivalant to 67.4% of the total net-production of 598.8 TWh.

[22] equivalant to 51.5% of the total net-production of 581.3 TWh.

of EUPHEMIA might offer a chance to reduce market concentration. As it is operated in one central location, it actually facilitates the market entrance and the coexistence of PXs. Even if two or more PXs were operating in the same market area, EUPHEMIA would ensure that there is only one corresponding reference price. Hence, PXs could compete on trading fees or quality of service.

1.3 Cross-border trading and redispatch

Unlike US-pool systems which are based on nodal pricing, power trading in Europe is organised in market areas. For Germany as for most other European countries, the market zone is identical with its corresponding national borders[23]. However, the Scandinavian countries Denmark, Sweden and Norway, the UK and Italy feature more than one market area within their national borders. This section covers cross-border trading between market areas as well as redispatch measures within market areas.

1.3.1 Explicit cross-border trading

After regulation (EC) No 1228/2003 went into force, non-market based congestion methods had to be replaced all over Europe by non-discriminatory market-based regimes such as implicit and explicit auctions. The process of explicit cross-border trading usually involves two stages. In a first step, the right to use cross-border capacity is sold to market participants via an UPA. The second step, is to then schedule a power flow from one market area to another by exercising either all or some fraction of the transmission rights. Even though explicit-auctions are considered to be market-based when compared to regimes such as *first-come, first-serve (FCFS)* or pro-rata, there is still a multitude of challenges they are facing.

First, they allow for the exertion of market power by dominant players or incumbent generators. Bunn and Zachmann (2010) analytically construct a case in which a dominant player can profit from misusing transmission capacity. They also empirically analyse actual transmission schedules at the Anglo-French interconnector (IFA) and describe evident inefficiencies which may be a result of market abuse. Gebhardt and Höffler (2013) find that well informed traders at the Danish-German and Dutch-German border seemed not to engage in cross-border trading in the years 2002-2006 which could be a sign of cross-border collusion. Additionally, market participants can face uncertainty about the actual demand for power transmission as spot prices of connected markets are not known at the time they bid for cross-border capacities and schedule power flows.

[23] including Austria.

This observation is confirmed by Zachmann (2008) and Dieckmann (2008) who add that the timing of DA-PXs of connected markets also plays an important role and adds to the poor performance. Richter and Viehmann (2014) identify another source of inefficieny. Even in the absence of a dominant player misusing or blocking capacity and in the absence of incomplete information with respect to the precise demand for power transmission, market participants play a Bayesian-Cournot game resulting in reduced power transmission that is not maximising social welfare[24]. Additionally, they show that asymmetric capacity endowments among market participant and incomplete information with regard to the number of competing rivals and their endowments further reduce efficiency[25].

Even though European harmonisation has come a long way, there are still cross-border capacities within Europe that are auctioned off daily by the means of explicit cross-border auctions. While this is true mainly for Eastern and South-Eastern European interconnectors, some German and Austrian[26] interconnectors are affected as well. Daily transmission rights to and from Poland, Czech Republic, Hungary and Switzerland are still being sold explicitly.

1.3.2 Implicit cross-border trading

Through implicit auctions, the auctioning and subsequent use of transmission capacity is implicitly integrated into the clearing process of DA-PX auctions who minimise price spreads between connected market areas. Implicit cross-border trading, which is often referred to as market coupling or market splitting, guarantees optimal flows (within the *Available Transfer Capacities (ATC)*) that maximise social welfare of connected market areas. Not surprisingly, the latest regulation (EU) 2015/1222[27] states that all DA-cross-border capacities shall be allocated via implicit auctions. However, it's implementation was difficult to facilitate as long as national PXs used their own algorithms and closed their order books at different times. Weber et al. (2010) and Meeus (2011a) provide a good overview about the complexities of the implicit auction implementation process. The first successful international market coupling in Europe that involved more than one PX began in November 2006. The so called Tri-Lateral Market Coupling (TLC)

[24] for additional information on interconnector economics see Turvey (2006) and Richter and Viehmann (2014).

[25] all of these issues refer to daily DA explicit cross-border auctions. Long term auctions for monthly or yearly capacity are not affected as capacities that are not used are handed back to the auction office and sold again in daily explicit or implicit auctions (use-it-or-lose-it principle).

[26] currently, there is not bottleneck between Germany and Austria, hence both countries are considered to be one market area with identical prices.

[27] Commission Regulation (EU) 2015/1222 is establishing a guideline on Capacity Allocation and Congestion Management (CACM).

connected the French, Dutch and Belgian market areas. It took four more years, a consolidation of PXs[28] and an alignment of order book closure times before the German market area joined in November 2010 and the *Central Western European Market Coupling (CWE)* went live. At the same time, the Scandinavic region operated by Nordpool was connected to CWE via the Interim Tight Volume Coupling (ITVC).

This fragile interim solution was later replaced by the PCR-initiative that went live in February 2014[29]. The implementation of PCR is considered to be an important milestone in the integration of European spot markets, as it is facilitated by one single algorithm EUPHEMIA (EPEX Spot et al., 2016) that includes all features of the PXs connected as well as the calculation of cross-border flows and is designed to maximise social welfare. It is also open to include further market areas such as Switzerland and Eastern and South-Eastern European countries.

While ATC-based market coupling is currently used at most European borders, the target model (see regulation (EU) 2015/1222) aims at the implementation of so called *FBMC*. In ATC regimes, available cross-border capacities are being disclosed separately for each border. They are calculated ex-ante based on heuristic rules and d-2 estimates (Bergh et al., 2015). As actual flows at other borders are unknown at the time of ATC-calculation, security margins tend to reduce ATCs when compared to actual physical capacities. FBMC on the other hand is a more integrated approach that takes into account the important constraints of a meshed network (also within market areas). TSOs ex-ante calculate Remaining Available Margins (RAMs) of critical lines and zonal Power Transfer Distribution Factors (PTDFs), the actual flows are then determined during the DA market clearing process (Bergh et al., 2015). As critical lines and their interdependencies are explicitly considered, actual cross-border flows are higher when compared to ATC which in turn decreases price spreads and increases social welfare. As the implementation of FBMC is very complex, it started in May 2015 for the CWE countries only within the larger PCR, but more market areas are expected to join in the future. FBMC can result in non-intuitive flows from high into low price market areas. Due to political concerns[30], EUPHEMIA (EPEX Spot et al., 2016) currently does not allow non-intuitive flows.

[28]the French Powernext and the German EEX merged and created EPEX Spot in 2008.

[29]at the same time, Great Britain was included into the market coupling. Later, Spain, Portugal (both in May 2014) and Italy (in February 2015) joined in.

[30]Even if non-intuitive flows maximise overall social welfare, market areas that export even though prices are higher obviously feel disadvantaged.

1.3.3 Intraday cross-border trading

There are two main differences with regard to the allocation of intraday and DA cross-border capacities. To begin with, remaining unused capacities can be requested free of charge in intraday while congestion rents result from explicit and implicit DA auctions. Secondly, those capacities are allocated continuously to market participants or PXs (for intraday market coupling) and not via the means of an auction.

In 2010, EPEX established an implicit intraday market coupling between the French and the German market area. If intraday cross-border capacities are available, EPEX order books show bids and/or offers of the connected market zone and arranges for cross-border nominations if trades are concluded. In 2012, Austria was coupled to the German market, one year later the French-Swiss and German-Swiss borders were included as well.

In late 2014, several PXs (including EPEX) and TSOs (including all German TSOs) have started a common *Cross-border Intraday Market Project (XBID)* which is currently expected to go live in the second half of 2017. XBID aims at creating one central intraday trading platform for cross-border capacities in a transparent, efficient and cost effective manner (ENTSO-E, 2016). It shall facilitate explicit allocation to market participants as well as continuous implicit allocation via shared order books of all PXs connected to the system using the FCFS-principle. Neuhoff et al. (2016) challenge the fact that XBID focuses solely on continuous markets. They propose the introduction of intraday auctions that might allow for a more efficient allocation of scarce cross-border capacities including congestion rents very similar to implicit DA auctions (see Section 1.3.2). They argue that auctions would favour efficient traders while the FCFS rule in continuous markets favours the most rapid ones. However, the latest EU regulation 2015/1222 on CACM targets towards continuous implicit allocation in intraday markets only, leaving little space for the implementation of intraday cross-capacity auctions. The regulation is also likely to terminate the explicit allocation to market participants which is currently still an element of the XBID project. On the other hand, the transition from ATC-based to FBMC is also requested by the regulation, however currently not foreseen in XBID.

1.3.4 Redispatch

After liberalisation and unbundling took place, the vertical planning approach within the power industry was abandoned. Most new production capacities such as coal and wind generation were build in the North of Germany. The location close to the sea is more profitable as shipping costs of coal are lower and wind speeds are on average higher than in Southern Germany. During the same period of time, several nuclear production units in Southern Germany had to shut down. Due to a lack of coordination, the high-voltage transmission grid that is transporting power to the demand centers in West and South Germany was not extended with a similar pace.

As long as Germany remains one market area, temporary congestions within the price zone are solved by the means of cost-based redispatch of conventional units and the curtailment of renewable generation (so called Einspeisemanagement). While generators with highest marginal costs are being ordered to ramp down in the area with excess production, generators with lowest marginal costs have to ramp up in the region with excess demand. The resulting costs are aggregated by the TSOs and passed through to end-consumers. A very detailed explanation of redispatch economics is given by Nüssler (2012) and Burstedde (2012). According to a report by the *Bundesnetzagentur for Electricity, Gas, Telecommunications, Post and Railway (BNetzA, 2016)*, combined volumes of redispatch and curtailment of renewables more than tripled from 6.8 TWh to 20.8 TWh in 2015 when compared to 2014. Associated costs more than doubled from 368 m€ to 881 m€. In 2009, costs of redispatch were as low as 25 m€ (BNetzA, 2010).

The precise definition of the term *cost* in cost-based redispatch is a contentious issue between production unit owners on one side and regulators as well as TSOs on the other. According to the German Energiewirtschaftsgesetz (EnWG, § 13a), there must be an adequate compensation for redispatch measures. The latest enactment (BK8-12-019) by BNetzA that defines adequate compensation was repealed in August 2015 after a court[31] ruled that reimbursement for redispatch measures was too low. The main controversial subjects are whether, and if so to which extent, fixed costs and capital costs shall be taken into account. A famous example on the complexity of redispatch compensation was the so called *Lex Irsching*. As the owners planned to mothball two highly efficient newly build CCGTs in Irsching due to lack of profitability, a special agreement was found to split fixed and capital costs according to the energy produced under redispatch and market-driven operations, respectively (Bundeskartellamt, 2015). This led to the incentive for operators to include fixed and capital costs into their variable generation costs. As a result, the market-driven production was reduced to a minimum and the main share of fixed and capital costs had to be covered by the TSO. Due to these inverse incentives, this special agreement was also repealed.

Even though European regulation allows for reviewing of existing market zone configurations[32] and EUPHEMIA is able to facilitate a splitting of the German market area, the establishment of more than one price zone within Germany is currently unlikely due to political concerns with regard to price differentials in Germany as well as fear of

[31] decision by OLG Düsseldorf, VI-3 Kart 313/12 (V).
[32] see § 32 of regulation (EU) 2015/1222.

reduced liquidity (BMWi, 2014). However, the planned split of the German-Austrian price zone in summer 2018 proposed by the *Agency for the Cooperation of Energy Regulators (ACER)* might be a first step in this direction. More radical approaches to reduce redispatch would be the implementation of nodal pricing or of market areas independent of national borders as proposed by Burstedde (2012) for CWE. Both proposals would require a high level of European harmonization with regard to intraday trading and balancing markets prior to implementation. Furthermore, the introduction of nodal pricing would presuppose a switch from a self-dispatch to a central-dispatch system and might be associated with significant switching costs (Egerer et al., 2015). The introduction of price zones independent of national borders as proposed by Burstedde (2012) might be a feasible compromise as the main features of the current self-dispatch system could be maintained, price zones would be sufficiently large not to compromise liquidity and redispatch would be reduced significantly.

As long as Germany remains one price zone, volumes and costs of redispatch are expected to further increase. Strikingly, the actual redispatch costs significantly outpace forecasts by Nüssler (2012) and Trepper et al. (2015), as their cost predictions for 2020 were already exceeded in 2014. This might be due to the reason that low-cost redispatch potential is highly overestimated in these studies. Generation units close to the marginal price are typically used to provide AS (see Section 1.5) and hence the potential for redispatch is limited. While the loss of social welfare through redispatch is usually considered to be negligible (see e.g. Trepper et al. (2015)) but might be underestimated due to the same reasons as state above, its distributional effects are indisputable. A split into Northern and Southern market zones would reduce wholesale prices in the North and increase prices in the South. In Northern Germany consumer rents were increasing and producer rents were decreasing, while in Southern Germany the opposite would be the case.

1.4 Intraday trading

Intraday trading covers the timeframe between the closure of DA markets (in Germany at 2.30 p.m.) and the intraday gate closure shortly before start of delivery. Market participants use intraday trading to balance deviations of their DA schedules which result from updated production or consumption forecasts. Intraday cross-border trading is covered in Section 1.3.3.

1.4.1 OTC versus Exchange based trading

To the author's knowledge, there is no data available on historical volumes of OTC-based intraday trading. However, prior to the implementation of an intraday trading system by EPEX in 2006, all intraday trades were conducted OTC, mainly via telephone. In its first full year of operation 2007, total traded volumes at EPEX were significantly below 1 TWh according to Rademaekers et al. (2008). With the increase of renewable production units (see Section 1.2.4), improved intraday cross-border trading opportunities (see Section 1.3.3), the reduction of intraday lead times (see Section 1.4.2) and the rise of automated trading (see Section 1.4.3), traded volumes at EPEX have increased enormously to 59.0 TWh in the German/Austrian market area in 2015[33]. According to a survey of market participants, volumes of OTC intraday trades are negligible when compared to EPEX nowadays. The same holds true for the Nordpool intraday system ELBAS, which facilitates intraday trades in Germany as well.

1.4.2 Market design

Intraday products in Germany as well as in most neighbouring countries are traded continuously, being also the predominant type of trading for most securities in the wider financial markets. Bids (buy orders) and offers (sell orders) can be placed continuously in an open order book of the corresponding trading system. The orders will either be matched (filled) immediately if there are suitable open orders in the market or they remain as open (limit) orders in the open order book. Intraday trading at EPEX starts at 3 p.m. in DA[34]. The intraday lead time marking the time gap between intraday gate closure and start of delivery has been reduced from 45 to 30 minutes for all hourly and quarter hourly products in July 2015[35]. Reduction of intraday lead time is considered to be an important step to decrease overall system costs and increase efficiency. Forecasts of production and consumption schedules are getting more precise the closer they are to the time of delivery, this is particularly true for fluctuating renewable production. In the long-term, this reduces the need for balancing energy (see Section 1.6) which reduces the demand for capacity procurement of AS.

Neuhoff et al. (2016) propose to rethink and to discretise the current intraday market design of continuously traded products. They believe that the introduction of intraday auctions similar to those conducted in the DA market alleviates several critical issues

[33] according to press releases by EPEX, volumes have increased from 10.2 TWh in 2010 to 15.8 TWh in 2012 to 47.1 TWh in 2014.

[34] start of trading of quarter hourly products has been shifted to 4 p.m. due to introduction of the quarter hourly auction (see Section 1.2.2).

[35] in March 2011, the lead time has been reduced from 75 to 45 minutes.

with the current set up. First, they would allow for a fair allocation of intraday cross-border capacities (see Section 1.3.3). Second, an UPA would create a tradable index. Today, most indexed intraday contracts reference to the volume weighted average price of all trades conducted in the continuously traded market. As explained by Neuhoff et al. (2016), this creates a basis risk as the price of any discrete transaction is very likely to deviate from the index price. Third and most important, it would secure operational fairness and reliability (see Section 1.4.3) and put an end to the race to react fastest. In the context of wider financial markets, Budish et al. (2014) argue that any market using continuous order books eventually ends up in a *"socially-wasteful and liquidity-reducing speed race"*. This is due to the fact that all messages are processed one-at-a-time in the order of arrival, giving an advantage to those who are able to react most quickly. According to Budish et al. (2014), this can result in order withdrawals or wider spreads of slower liquidity providers. Hence, they propose so called *Frequent Batch Auctions (FBAs)* as an alternative market design, which basically consists of a frequent sequence of sealed-bid UPAs. It remains to be seen whether FBAs are a viable option to replace continuous order books in wider financial markets as well as for intraday power trading.

1.4.3 Operational efficiency and roboter trading

In 2012, EPEX opened its intraday trading system via an *Application Programming Interface (API)* to market participants. Using this new communication channel[36], market participants can send and receive standardised messages to and from the PX server. Independent software vendors and market participants themselves began to develop software and programmed algorithms that facilitate automatic trading. As described by Neuhoff et al. (2016), the increasing number of market participants using automated trading algorithms led to higher trading speeds[37], higher turn-over rates but also to higher *Order-to-Trade Ratios (OTRs)*[38]. As EPEX servers were not originally designed to cover this increased load, poorly designed trading algorithms or just a surge in activity can result in backlog and processing delays (Neuhoff et al., 2016) or even system crashes that might interrupt intraday trading for several hours.

Hence, EPEX is currently trying to find the right balance between order limitations which might also reduce liquidity and a fair, safe and reliable operation of the trading servers. A first attempt in 2015 to limit the maximal number of order modifications per

[36] while EPEX was the first PX in Europe to provide an API, the concept of APIs is not new in the wider financal markets.

[37] according to Budish et al. (2014), the time scale and reaction times of computer traders are in an order of magnitude of 0.0001 seconds nowadays.

[38] the OTR shows the ratio of order submissions or modifications per trade that has been actually concluded.

market participant per day, per minute and per second was doomed to fail as it was non-binding. As of April 2016, EPEX introduced a binding OTR of 20 per contract which was increased to 50 in August 2016, charging extra fees to those who exceed limits. At the same time, EPEX is working on further system modifications to improve performance. In June 2016, the tick size was increased from 0.01 to 0.10 €/MWh. This measure intends to reduce the number of order modifications as it prevents market participants outbidding each other by economically negligible amounts (Budish et al., 2014). Additionally, EPEX is upgrading its intraday trading systems to be able to cope with the increased number of messages.

1.5 Ancillary Services

Balancing capacities for the provision of ancillary services are procured by TSOs on a daily and weekly basis in Germany. TSOs then call for the activation of balancing energy to balance any real-time deviations (see Section 1.6). In Germany, there are three types of AS, *Primary Reserve (PR)*[39], *Secondary Reserve (SR)*[40] and *Minute Reserve (MR)*[41], which differ with regard to activation times and delivery periods. While PR needs to be fully activated latest after 30 seconds, full activation time of SR and MR is 5 and 15 minutes respectively[42]. German TSOs commonly determine and publish the capacity demand for the respective AS products. They conduct weekly auctions for one symmetric PR contract, weekly auctions for four separate SR contracts [43] and daily auctions for 12 separate MR contracts (see also figure 1.1).

1.5.1 Capacity procurement

According to Heim and Götz (2013), the four German TSOs began to jointly procure MR capacity via an web-based auction in December 2006. One year later, capacities for PR and SR were also procured via the common platform *regelleistung.net*. Prior to that, each TSO was individually procuring balancing capacities within its control area[44]. From 2008 to 2010, the four German TSOs formed a so called *Grid Control Cooperation (GCC)* in order to create one common market. The GCC consisted of four modules. The first module aimed at preventing counteracting control reserve activation (see Section 1.6.5).

[39]also referred to as Frequency Containment Reserve (FCR).

[40]also referred to as Automatic Frequency Restoration Reserve (aFRR).

[41]also referred to as Tertiary Reserve or Manual Frequency Restoration Reserve (mFRR).

[42]for more technical details, visit the website *regelleistung.net* or ENTSO-E (2014).

[43]the contracts for upward and downward regulation during peak times on weekdays (8a.m. to 8p.m.) are referred to as PosHT and NegHT, during off-peak times they are referred to as PosNT and NegNT.

[44]according to Müsgens et al. (2014), procurement of AS in Germany via competitive auctions first started in 2002.

The second module, the common dimensioning of balancing capacities has led to a significant reduction in demand for SR and MR capacity and hence to a reduction in procurement costs (see Section 1.5.4). The common procurement of SR (Module 3) aimed to increase competition between *Balancing Service Providers (BSPs)*. Module 4 completed the common market by introducing on single merit-order list for energy calls (see Section 1.5.2).

According to the national legislation[45], German TSOs procure balancing capacities via PABAs from market participants. In PABAs, also referred to as Discriminatory Price Auctions (DPAs), each successful bid is paid its bidding price. This design is fundamentally different compared to UPAs used by DA-PXs (see Section 1.2.2), in which each successful bid is paid the marginal clearing price. The relative performance of these two auction types both in terms of efficiency and prices has been a controversial issue not only in the energy related literature for many years. This is true in particular for more complex market settings such as the one in German AS markets. As TSOs procure several units of the same good and market participants can place several bids, this auction type is also referred to as *MUMB* auction. Classical closed-form solutions of single-unit auctions cannot be transferred to MUMB auctions as bidders have an incentive to shade their bids (Krishna, 2002).

Using a variety of settings and approaches, Fabra et al. (2006) and Frederico and Rahman (2003) find that PABAs tends to reduce consumer prices while the affect on welfare is ambiguous. Heim and Götz (2013) and Rassenti et al. (2003) on the other side prefer UPAs. They argue that repeated PABAs lead to higher consumer prices as bidders tacitly collude or repeatedly bad guess prices. In a more qualitative analysis, Kahn et al. (2001) argue that PABAs lead to higher transaction costs as every bidder has to forecast the estimated marginal price, reduce efficiency as some low-marginal cost bids might bid to high and are rejected and disadvantage small players as they have higher forecasting costs and benefit less from the exertion of market power by large players. To the author's knowledge the most detailed analysis of PABA versus UPA in a setting that is very comparable to the German AS market was conducted in chapter 4 using an agent based approach. They find that UPAs lead to higher consumer prices for all market settings, with price differentials being largest at medium demand to supply ratios as players in UPAs significantly increase prices even if none of them is pivotal. They conclude that UPAs are favourable in competitive markets with many players while PABAs should be used in highly concentrated markets with few and asymmetric players.

[45] according to § 8 of Stromnetzzugangsverordnung (StromNZV) from 2005, PABA have to be used to procure balancing capacity.

In § 39 of *Network Code on Electricity Balancing (NCEB)*, the *European Network of Transmission System Operators for Electricity (ENTSO-E)* is stating that the procurement of balancing energy shall be based on marginal pricing (UPAs), *"unless TSOs complement the proposal with a detailed analysis demonstrating that a different pricing method is more efficient..."*(ENTSO-E, 2014). To our knowledge, German TSOs so far have neither started an initiative to change from PABA to UPA, nor are they working on a detailed analysis to prove that PABAs are more efficient.

1.5.2 Energy prices and scoring rules

Suppliers of SR and MR capacities bid not only a capacity price, but also a corresponding energy price. In the first step, TSOs select all bids according to the ascending order of capacity prices in a PABA. In a second step, they reorder all winning bids according to their corresponding energy prices. In case TSOs call for upward (downward) regulation, suppliers are selected according to the ascending (descending) common energy merit order. Each supplier that is called to deliver balancing energy is compensated with her bid price. As energy volumes are rather negligible, there is no corresponding energy price bid and hence no separate remuneration for actual energy calls in PR.

The current scoring rule - the stepwise selection of AS bids in combination with PABA - comes in for criticism as corresponding energy price bids are completely ignored in the first step. Müsgens et al. (2014) illustrate that AS markets are only efficient if those BSPs provide AS whose combined costs of providing balancing capacity and delivering expected balancing energy are lowest. Based on the theoretical work by Chao and Wilson (2002), Müsgens et al. (2014) conclude that current scoring rule was efficient with the following presuppositions. First, rational suppliers subtract their expected revenues generated by energy calls from their capacity provision costs. Hence, capacity bids are expected to include energy revenues and lowest cost providers shall be accepted. Second, it is assumed that markets are sufficiently competitive and accurate computations of expected profits from energy calls can be made. Müsgens et al. (2014) argue that UPAs for both capacity and energy prices would be required in order to generate accurate estimations of expected profits from energy calls as PABAs reduce transparency and increase complexity. However, we add that they do not address the incentive of bid shading and the resulting inefficiencies in MUMB-UPAs as shown by Krishna (2002). Swider (2007) proposed an alternative scoring rule that takes into account capacity and the corresponding energy price bid using a duration curve approach for expected energy calls. However, German TSOs have so far rejected the introduction of more complex scoring rules as they might result in non-intuitive outcomes and even more complex bidding strategies.

NCEB by ENTSO-E (2014) gives no clear guidance whether supplier of balancing energy should be compensated with their energy bid price or the marginal price. In fact, §§ 53 do not mention any preferred remuneration methodology at all.

1.5.3 Timing of AS products

The length of the product period and lead time between the capacity auction and the start of delivery are two crucial factors when it comes to the design of AS markets. Müsgens et al. (2012) show how a reduction of product length increases efficiency. They demonstrate that it is most efficient to provide AS from power plants with marginal costs close to the hourly DA-PX price. The longer the bidding length of the product period is, the more hourly price vary. Hence, provision costs of any given power plant increase and efficiency decreases. An alternative point of view is that large players with a diverse generation portfolio profit from longer product periods as they tend to have generation assets close to the marginal price more often (Knaut et al., 2017). Smaller players with only one production unit or technology are disadvantaged though. The situation is very similar with regard to the lead time. The longer the lead time, the higher is the uncertainty about future DA prices and hence AS provision costs. Again, small players with only one production unit are disadvantaged as they have to commit to a state of operation if they sell AS well in advance, not knowing actual spot price realisation.

In Germany, the length of the product periods for PR and SR[46] are both one week. As the auctions take place on Tuesday and Wednesday afternoons the week before (see figure 1.1), lead times are more than five and four days respectively. For MR products, the product period is only 4 hours. There are six blocks of upward and six blocks of downward regulation that cover a timeframe of 4 hours each and the auction is the day before delivery at 10 a.m. Hence the lead time is between 14 and 34 hours[47]. In an effort to integrate renewable production units into AS markets and to increase efficiency, BNetzA is currently discussing to further reduce lead times and the lengths of product periods.

1.5.4 Transparency and market structure

Unlike in energy only markets, transparency levels in AS markets are low and recent information about market structure and market power can hardly be obtained. German

[46] before November 2011, the length of the product period for both PR and SR was 1 month, lead time was about two weeks (Müsgens et al., 2012).

[47] as there are no auctions on weekends and public holidays, lead times are larger for Sundays, Mondays, public holidays and days after public holidays.

TSOs keep transparency on a minimum level trying to avoid pivotal players to exercise market power. TSOs do not publish a list of the individual units prequalified to provide AS, but merely a list of all BSPs on a firm level. It is also unknown which smaller units from other providers are pooled and offered. Firms might be able to obtain some information regarding the general availability of generations units larger than 100 MW, which are assumed to be able to provide AS via mandatory messages about planned and unplanned non-usability of generation units[48]. However, even if a unit is available to produce power in the energy only market, specific technical reasons known only by the owner might prevent it from being able to provide AS.

In April 2011, BNetzA decided to further reduce transparency by modifying the auction rules of SR (BNetzA, 2011). BNetzA decided not to publish non-accepted extra-marginal bids anymore, only accepted infra-marginal bids ought to be displayed to the market. As a result, market participants do not know about the supply to demand ratio and have difficulties detecting scarcity in the market[49]. The agency believed that knowledge of extra-marginal bids might have led pivotal players to increase their bids in case of scarcity and that reduced transparency was the lesser of two evils. As BNetzA is mainly concerned about low consumer prices, we show in chapter 4 that reduced transparency about the actual supply to demand ratio results in lower prices, especially if market concentration is high and few large players dominate. Inefficiencies arising from reduced transparency in PABA such as higher transaction costs for price forecasting and low-cost players bidding to high are difficult to quantify and not in scope of BNetzA.

Data on market structure in German AS markets is mostly outdated. Growitsch et al. (2010) received anonymised bidding data for MR by BNetzA for the year 2008. Their study focuses mainly on the degree of market concentration. Applying traditional measurements of market concentration such as the *Herfindahl-Hirschman-Index (HHI)* and *Concentration Ratios of the n suppliers with the highest market shares (CRn)*, they find that the market concentration was high for most MR products. The *Pivotal Supply Index (PSI)* reveals that the most dominant player is pivotal in 12 and 14 percent of all auctions for the two negative MR products during the night NEG_00_04 and NEG_04_08 respectively. Whether the high degree of market concentration led to an abuse of market power by dominant suppliers was not investigated by Growitsch et al. (2010). Similarly, Heim and Götz (2013) received anonymised SR bidding data by BNetzA for the years 2009 and 2010. Focusing on the SR NegNT product which was subject to significant price increases during that time, they analyse market structure, bidding behaviour and search for evidence of market abuse. Applying HHI and CRn, they find that the market was highly concentrated. Additionally, the PSI reveals that the most dominant supplier

[48]data can be found on the website eex-transparency.com.
[49]while extra-marginal bids for PR are not published either, extra-marginal bids in MR are published.

was pivotal in 100 percent of all auctions, while the second and third largest suppliers were pivotal in more than 80 percent of all auctions. They conclude that the reduction of supply by the largest BSP and thereafter a form of implicit collusion by the two most dominant providers led to an increase of prices. Heim and Götz (2013) argue that legal prosecution of abusive behaviour by authorities is not feasible as providers can hide behind the guess-the-clearing-price principle in PABAs.

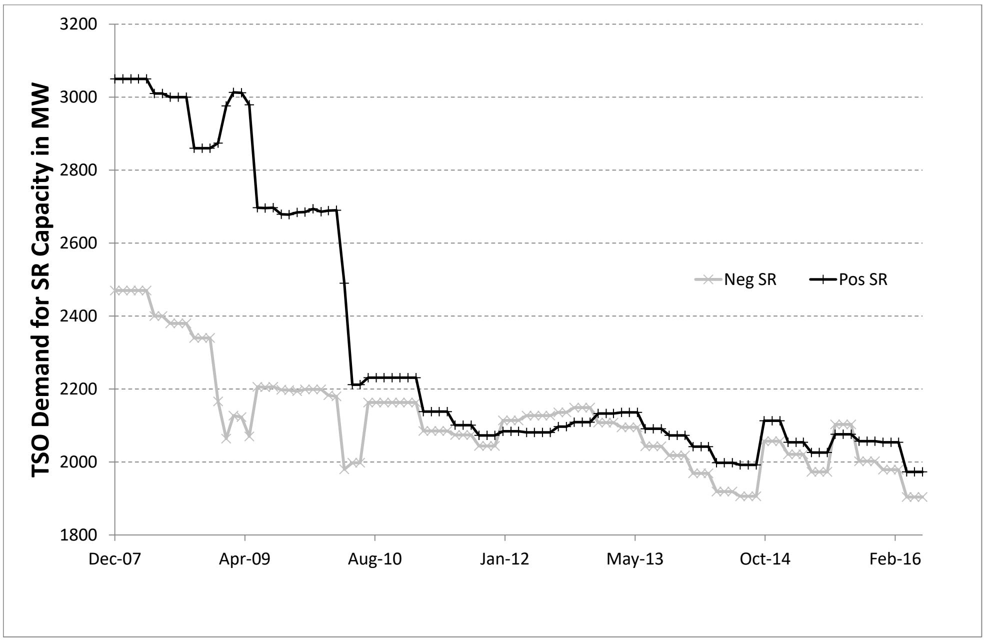


FIGURE 1.2: Development of TSO demand for SR capacity based on data provided by regelleistung.net. Temporary demand increases for Christmas and New Year's Eve weeks as well as for the solar eclipse in March 2015 are not considered

Even though there is no precise recent data on market structure obtainable, there are some facts pointing towards a reduction of market concentration in recent years. First, the successful implementation of GCC led to a subsequent reduction of demand for MR and SR. As shown in figure 1.2, demand for positive (negative) SR was reduced from 3050 MW (2470) end of 2007 to 2231 MW (2163) end of 2010. During the last 3 years, average demand was slightly above (below) 2000 MW, equivalent to a reduction of 33 (20) percent when compared to the initial levels of 2007. Second, the number of prequalified providers has been increasing. Within the last five years (May 2011 to May 2016), the number of PR providers more than tripled from 7 to 23, the number of SR providers almost quadrupled from 9 to 35 and the number of MR providers increased from 26 to 47 (see table 1.1). The reduction of demand and the increase of suppliers are likely to be the main drivers for steadily declining capacity prices especially for negative MR and SR in recent years. Furthermore, Knaut et al. (2017) discuss how a shortening of product periods might alter the level of market concentration. They find that average market concentration tends to decrease with shorter (daily or hourly) product periods. However, they also argue that single product periods exist in which the level of market concentration is higher than for longer (weekly) product periods.

	Number of prequalified providers			
	May 2011	March 2013	July 2014	May 2016
Primary Reserve PR	7	14	20	23
Secondary Reserve SR	9	19	27	35
Minute Reserve MR	26	36	38	47

TABLE 1.1: Development of the number of AS providers in Germany based on data provided by regelleistung.net)

1.6 Balancing Energy Market

Any deviations from the planned (production or consumption) schedules, that have to be submitted by each *Balancing Responsible Party (BRP)* latest at gate closure, are defined as Imbalances and are usually balanced by the TSO. In the final draft of NCEB, ENTSO-E (2014) defines balancing as: *"all actions and processes, on all timescales, through which Transmission System Operators ensure, in a continuous way, to maintain the system frequency within a predefined stability range..."*. Hence, TSOs procure beforehand Balancing Capacity from BSPs (see also Section 1.5) and then call for the activation of Balancing Energy in case of real-time imbalances. BRPs have to pay for any imbalances they are responsible for while BSPs get compensated for the activation of balancing energy.

There is a variety of different balancing system designs across Europe with regard to the imbalance-price system, the settlement period, publication of the balancing signal and the netting of imbalances. ACER and ENTSO-E (2014) have developed a framework in order to foster harmonisation. However, the ENTSO-E Roadmap spans to the end of this decade and some differences are likely to persist even longer due to national idiosyncrasies of power markets in the member states. Unlike in most neighbouring countries, a one-price system for imbalance price calculation is in place in Germany.

1.6.1 One vs. two-price systems

Self-dispatched systems can be divided in two-price and one-price arrangements. The distinct feature of two-price systems is that there are two prices for balancing energy at all times independent of the status of the overall system. Using notations from Vandezande et al. (2010), the common imbalance settlement schemes in two-price systems are shown in table 1.2. If the overall system is short and a BRP contributes by being short as well, she has to pay the price for upward regulation p_u multiplied with a penalty factor $penalty_u$. Another BRP being long at the same time reducing the overall system shortage will receive some index price, usually the DA price p_{DA} of the energy-only market with $p_{DA} < p_u$. If the overall system is long and a BRP contributes by being long as well, she receives the price for downward regulation p_d divided by a penalty factor $penalty_d$. Another BRP being short at the same time reducing the overall system imbalance will pay the DA-price p_{DA} with $p_{DA} > p_d$.

		Two-Price System		One-Price System	
		System Imbalance		System Imbalance	
		Negative (short)	Positive (long)	Negative (short)	Positive (long)
BRP Imbalance	Negative (short)	$+P_u*(1+penalty_u)$	$+P_{DA}$	$+P_u$	$+P_d$
	Positive (long)	$-P_{DA}$	$-P_d/(1+penalty_d)$	$-P_u$	$-P_d$

TABLE 1.2: Balancing settlement schemes in two-price and one-price system based on Vandezande et al. (2010) with p_u = price for upward regulation, p_d = price for downward regulation, p_{DA} = DA-price, $penalty_u$ = penalty for upward regulation and $penalty_d$ = penalty for downward regulation

Two-price systems are implemented by TSOs, whose main focus is system security and not economic efficiency. BRPs are incentivised not to deviate from their nominations before gate closure and deterred from engaging in speculations between energy-only and balancing markets as trading profits are nearly impossible to generate (see also Boogert and Dupont (2005)). However, adverse effects on economic efficiency in two-price systems are widely spread and well documented by Barth et al. (2008), Belmans et al. (2009) and Vandezande et al. (2010).

Prices for upward regulation are often more expensive than for downward regulation. As a consequence, penalties for upward regulation in two-price systems are usually higher than for downward regulation. Hence, BRPs tend to buy more than the naturally induced level in the energy-only market in order to avoid short positions in the balancing market (see Belmans et al. (2009)). This behaviour results in higher prices in the DA market. Furthermore, BRPs with load and generation assets in their portfolio can be incentivised not to provide balancing services to the TSO but keep the option for upward regulation for their own use. In a worst case scenario, all BRPs would keep a back-up for their own portfolio instead of offering it to the TSO resulting in a very inefficient overall state of the system (see Vandezande et al. (2010)).

Imbalance settlement schemes in one-price systems are shown in table 1.2. If the overall system is short and a BRP contributes by being short as well, she has to pay the price for upward regulation p_u. Another BRP being long at the same time reducing the overall system imbalance will receive the same price p_u. If the overall system is long and a BRP contributes by being long as well, she receives the price for downward regulation p_d. Another BRP being short at the same time reducing the overall system imbalance will pay p_d. One-price systems are implemented by TSOs whose main focus is economic efficiency. BRPs are incentivised to deviate from their scheduled nominations if they are able to reduce the overall system imbalance by being long in case the system is short and vice versa. However, market rules need to prevent speculative trading that endangers system security and need to be designed in a non-discriminatory way.

1.6.2 Calculation of imbalance prices

One main concern, particularly in one-price systems, is the calculation of imbalance prices. The detailed calculation methodology of German *Bilanzausgleichsenergiepreise (reBaP)* is published by BNetzA (2012b)[50]. The main component of reBaP prices are the costs incurred by energy calls of SR and MR (see Section 1.5.2) and balancing energy delivered by the *International Grid Control Cooperation (IGCC)* (see Section 1.6.5). Additional rules prevent extreme price spikes and arbitrage opportunities with the energy only market (see Section 1.6.3). The fact that volume weighted average costs of the PABA energy merit order are used is in line with § 61 of NCEB (ENTSO-E, 2014) which states that the imbalance price for upward (downward) regulation *"shall not be less (greater) than the weighted average price for activated positive (negative) Balancing Energy for Frequency Restoration Reserves and Replacement Reserves..."*.

1.6.3 Arbitrage opportunities

Just and Weber (2015) show that system endangering trading profits resulting from speculations between energy-only (DA or intraday) and balancing markets to be possible in the German one-price balancing system. They argue that even though actual

[50] the latest version shall be published on the common TSO website regelleistung.net.

imbalance prices are published with a two month delay, expected imbalance prices for positive and negative imbalances can be estimated. Imbalance prices mainly consist of costs for energy calls of SR and MR. As energy merit order curves of AS (see Section 1.5.2) are known already before the DA spot market closes, expected imbalance prices can be computed. This led to some straightforward trading strategies in case spot prices were above expected imbalance prices for upward regulation $p_{DA} > p_u$ (and vice versa $p_{DA} < p_d$) in the past. Even though anti-abuse clauses exist, Just and Weber (2015) argue that if a large number of players was to exploit this opportunity by selling in the DA market and buying back in the balancing market (and vice versa for downward regulation) this would endanger system security as balancing capacity procured by TSOs is limited (see Section 1.5.1). Even if DA prices are in between expected regulation prices $p_d < p_{DA} < p_u$, Just and Weber (2015) demonstrate that there is an incentive to engage in stochastic arbitrage[51]. Another author describing arbitrage opportunities between energy only and imbalance markets is Möller et al. (2011).

End of 2012, BNetzA (2012a) decided to adjust the rules for the calculation of imbalance prices in order to curb the potential for system endangering trading strategies. The floor for upward and the cap for downward regulation was set to the hourly weighted average intraday price ($p_u \geq p_{Iday}$ and $p_d \leq p_{Iday}$) to limit the opportunity of straightforward arbitrage. Additionally, prices for upward regulation were increased by 50% (but at least 100) € if more than 80% of all procured balancing capacity was in use (and vice versa for downward regulation). This rule was intended to sanction those BRPs who increase total system imbalance in critical situations and to reward those BRPs who reduce it. Currently, BNetzA is in a consultation phase on how to further develop the imbalance price model in Germany as the usage of the hourly weighted average intraday prices still allows for profitable trading opportunities if deviations from the hourly weighted average intraday price are large enough. Additionally, quarter hours can be traded againt hourly contracts.

1.6.4 Real-time balancing signal

Publication of real-time data on the balancing signal is of crucial importance for a one-price system to work efficiently. Only if BRPs know their own position and the state of the overall system, they can actively steer their production or consumption into the right direction (see Section 1.6.1). To the author's knowledge, this issue is hardly covered by academic research though. ENTSO-E (2014)[52] merely states that TSOs shall publish *"the activated volumes of Balancing Services offered by TSO themselves*

[51] the closer DA prices are to imbalance prices, the larger this incentive gets.
[52] in § 8, paragraph 4.

no later than one hour after the operating period.". In contrast to the Belgium TSO ELIA and the Dutch TSO Tennet who publish information almost in real-time, German TSOs currently publish the average of activated quarter hourly volumes for upward and downward regulation with a delay of 15 minutes[53].

The question of how meaningful aggregated information about activated balancing volumes with a delay of 15 to 60 minutes is for BRPs to actively steer production or consumption remains subject to further research. However, it is clear without ambiguity that those BRPs that are BSPs at the same time receive real-time balancing activation signals from the TSOs[54]. As a result, they do have a significant advance of information compared to those BRPs who rely on public information. They can profit from real-time information while others have to rely on out-dated information. This fact is clearly discriminating, not efficient and can eliminated only by real-time publication of the balancing signal.

1.6.5 Netting of imbalances and IGCC

Netting of imbalances and avoidance of counteracting activation of balancing energy is a very powerful option to reduce balancing costs and increase overall system efficiency. While netting positions of BRPs within a control area is not a new concept, netting of imbalances across control areas was only introduced in 2008, when three of the four German TSOs[55] formed the GCC[56] to avoid counteracting activation of balancing energy (Module 1 of GCC, see Section 1.5.1). Expected cost savings of this cooperation were computed by Flinkerbusch and Heuterkes (2010).

Even though national imbalance price mechanisms are far from harmonised, this cooperation was later extended to the IGCC. According to common TSO plattform Regelleistung.net (2016), Denmark, Holland, Switzerland, Czech Republic and Belgium all joined the former national GCC during 2012. In April 2014 and February 2016, IGCC was further expanded to include Austria and France respectively. So far, netting of imbalances within the IGCC is only possible if cross-border capacities between connected control areas are still available after gate closure of intraday trading (see Sections 1.3.3 and 1.4). However, the final draft of NCEB by ENTSO-E (2014) even allows for the reservation of cross-border capacities for balancing purposes, if the socio-economic efficiency of this measure is proven. Cross-border reservations are likely to materialise only in case IGCC moves from the current simple netting of imbalances to a more integrated cooperation

[53] at their common website Regelleistung.net.

[54] BSPs receive the real-time balancing activation signals as they have to provide balancing energy.

[55] EnBW Transportnetze, TenneT TSO and 50Hertz Transmission or their legal predecessors respectively. In 2010, the fourth German TSO Amprion joined in as well.

[56] also referred to as Netzregelverbund.

which includes common rules for the procurement and dimensioning of balancing capacities as well as pricing mechanisms as already established within the German national GCC.

1.7 Conclusion

The answer to the pivotal question whether German short-term power markets work efficiently is ambiguous. Improvements in market design, increased trading activities and reduced market power by incumbent generators have certainly increased overall efficiency in recent years. The DA-market is certainly the most mature and efficient short-term power market, particularly since the clearing algorithm (EUPHEMIA) has been introduced which facilitates smart block bids as well as implicit FBMC. With regard to intraday markets, AS and Balancing energy, there is some potential for market design improvements and European harmonization.

However, two trends give cause for concern. Regulators who reduce transparency and hence overall efficiency in AS markets in order to reduce prices and increase consumer surplus. This trend should be reversed as markets mature and market power of incumbent generators vanishes. Secondly, non-marked based redispatch measures and other interventions by TSOs such as curtailment of renewable generation due to grid constraints have increased significantly in recent years. A worst case scenario would picture this development leading to a centrally planned power market. It remains to be seen whether nodal pricing, reconfiguration of existing market zones or even peer-to-peer transactions based on blockchain technologies in a decentral network will provide marked-based alternatives.

Risk Premiums in the German Day-Ahead Electricity Market

This chapter is based on Viehmann (2011)[57].

Abstract

This paper conducts an empirical analysis of risk premiums in the German day-ahead Electricity Wholesale Market. We compare hourly price data of the European Energy Exchange (EEX) auction and of the continuous over-the-counter (OTC) market which takes place prior to the EEX auction. Data provided by the Energy Exchange Austria (EXAA) has been used as a snapshot of the OTC market two hours prior to the EEX auction. Ex post analysis found market participants are willing to pay both significant positive and negative premiums for hourly contracts. The largest positive premiums were paid for high demand evening peak hours on weekdays during winter months. By contrast, night hours on weekends featuring lowest demand levels display negative premiums. Additionally, ex ante analysis found a strong positive correlation between the expected tightness of the system and positive premiums. For this purpose, a tightness factor has been introduced that includes expectations of fundamental factors such as power plant availability, wind power production and demand. Hence, findings by Longstaff and Wang (2004) can be supported that power traders in liberalised markets behave like risk-averse rational economic agents.

[57]Available here: https://doi.org/10.1016/j.enpol.2010.10.016.

2.1 Introduction

Within the last decade, the German and other European Power Markets underwent unprecedented transformations. Directives and regulations issued by the European Commission aimed to open markets, ensure non-discriminatory third-party access to power grids (Directive 2003/54/EC repealing Directive 96/92/EC) and to enforce cross border trading activities (Regulation 1228/2003) in order to harmonise prices and mitigate market power of national incumbent operators. An overview of the main regulatory issues related to European Electricity Markets and their recent progress was compiled in the *DG Competition Report on Energy Sector Inquiry* by the European Commission (2007). The report focuses on concentration, market power, vertical integration, market integration, transparency and price issues and it states that some progress has been made but many barriers to free competition still persist[58].

However, without any doubt the process of liberalisation led to an increase in power trading activities across Europe - particularly in Germany - Europe's largest economy and Power Market in terms of electricity consumption. Germany's annual power consumption amounts to 500-550 TWh. According to a recently published review of EU Wholesale Energy Markets by Rademaekers et al. (2008), estimated total annual trading turnover of German power contracts grew from 2,400 TWh in 2006 to 3,200 TWh in 2007. The fact that total trading turnover in 2007 amounted to around 6 times consumption can be seen as a sign of market maturity.

Nevertheless policymakers, regulators and public opinion in Europe remain suspicious of power trading activities (European Commission, 2009). This is partly due to the complexity of electricity trading and a lack of market transparency. As a result, the European Commission is addressing the issue to find which transparency requirements on trading activities are necessary to ensure a positive development of European Power Markets in accordance with the Directives and Regulations mentioned above (Rademaekers et al., 2008). As exchange based trading covers only a small fraction of the overall trading activities in most European countries, improved transparency in terms of market participants, traded volumes and prices of the OTC market would be beneficial for regulators and policy-makers in order to asses and monitor the functioning of European Power Markets.

Within this context, this paper conducts an empirical analysis of prices and premiums paid on the German day-ahead Power Market. In order to compare day-ahead EEX auction prices with prices of the preceding continuous day-ahead OTC trading, we decided

[58]For additional interpretation of the DG competition report, see London Economics (2007) and Ockenfels (2007).

to use price data provided by the Energy Exchange Austria (EXAA) as a snapshot of the continuous OTC market[59]. We find that positive and negative premiums for hourly contracts were paid only two hours prior to the final EEX auction. The average premium of daily delivery contracts represented by the Base block contract is slightly positive (0.61 €/MWh), but not statistically different from zero.

Premiums paid in electricity forward markets differ from those paid in markets for financial assets or storable commodities. This is due to one of the physical properties of power - it is not storable. While the constraint of non-negativity on inventory distinguishes financial assets from storable commodities, power markets are characterised by the absence of storage capacities in meaningful quantities at competitive cost. Therefore, power prices usually feature unique properties such as price spikes and heteroscedasticity[60]. For this reason, equilibrium models for commodities as described by Fama and French (1987) or Routledge et al. (2000) cannot be applied to electricity markets.

Authors such as Bessembinder and Lemmon (2002), Benth et al. (2008) or Pirrong and Jermakyan (2008) focus particularly on modelling equilibrium prices of forward contracts and risk premiums in electricity wholesale markets. Bessembinder and Lemmon (2002) present an equilibrium model that explicitly takes into account the physical properties of power and the convexity of the power production cost curve. According to their model, there are negative risk premiums for off-peak hours caused by low demand, little skewness and risk averse sellers. In peak hours however, buyers are willing to pay positive risk premiums due to the high demand and highly right skewed power prices. Benth et al. (2008) also develop a model that explains the existence of negative and positive forward premiums. However, their work has a different focus. They incorporate the changing relative eagerness of natural buyers and sellers to hedge their positions and test their model across different forward contract maturities.

An empirical analysis conducted by Longstaff and Wang (2004) largely supported implications by the Bessembinder and Lemmon (2002) equilibrium model in the case of the Pennsylvania, New Jersey and Maryland (PJM) Wholesale Market. By comparing hour-ahead and day-ahead prices for each hour, Longstaff and Wang (2004) found positive premiums for hours with highest demand and negative premiums for hours with low consumption levels. Although the set of data available for the German Power Market is somewhat different, we use a similar methodology as Longstaff and Wang (2004) in this paper. Pirrong and Jermakyan (2008) also propose a model to capture risk premiums - or as they denote it, the market price of risk - for power derivatives. Their analysis shows the presence of risk premiums at the PJM Market and the seasonality of these

[59] Described more in depth in section 2.3.

[60] For more details of power price properties see Weron et al. (2004), Bierbrauer et al. (2007), Huisman et al. (2007) or Douglas and Popova (2008).

premiums. Other authors who recently published empirical analyses of electricity market premiums include Hadsell and Shawky (2007), Douglas and Popova (2008), Lucia and Torró (2008), Botterud et al. (2010) and Redl et al. (2009).

The body of this article is as follows. Section 2.2 outlines the structure of the German Power Market and focuses particularly on the German Spot Market. Section 2.3 describes the set of data employed for the empirical analysis of premiums paid at the day-ahead market. In section 2.4, tests on the significance of these risk premiums are conducted and section 2.5 introduces a model that allows for the regression of ex ante measurements of risk on ex ante risk premiums. Section 2.6 provides interpretations of the results obtained in the two previous sections and section 2.7 concludes.

2.2 The German Power Market

The following section gives a short summary of the present state of the German Power Market and focuses in particular on the Spot Market, it's most important features, market places and trading participants. Germany represents Europe's largest Power Market in terms of consumption. The four largest electricity producers RWE, E.ON, Vattenfall and ENBW hold a market share between 70 and 85 percent[61]. There are four high voltage grids operated by four transmission system operators (TSOs). These 380 kV grids also represent the delivery points of power that is traded between market participants and on Power Exchanges. Congestion between and within the grids is currently tackled exclusively by redispatch of the TSOs. Other practices such as market splitting or nodal pricing[62] are not yet in focus. Today, the German Power Market is interconnected with a number of other European Power Markets of differing liquidity. Interaction between those markets requires transmission rights. Daily explicit day-ahead auctions are in place for interconnector transmission capacities to and from Poland, Czech Republic, Switzerland, Netherlands and France, Netherlands. Most of these countries also feature liquid exchange-based day-ahead trading, some have actively traded OTC markets. Market coupling and implicit auctioning of interconnector capacities between the German Market and the Nordpool[63] region, namely Sweden and Denmark, was established in late 2009. Market Coupling between Germany and France and Germany and Netherlands is scheduled to start in late 2010[64].

The two main market places for day-ahead trading in Germany are represented by the exchange EEX and electronic OTC trading platforms. Due to its high liquidity, EEX is

[61]See Lise et al. (2008) and Weigt and Hirschhausen (2008).
[62]See Brunekreeft et al. (2005) for concepts of market splitting and nodal pricing.
[63]Energy Exchange for the Scandinavian region.
[64]Go to www.epexspot.com for more details on the CWE Market Coupling Project.

widely regarded as the benchmark and reference point of the German day-ahead Power Market. The annual day-ahead volume increased from 88.7 TWh in 2006 to 127.3 TWh in 2007 and 154.5 TWh in 2008. Accordingly, daily spot trading volumes amounted to more than one quarter of the overall German energy demand in 2008. Like other Energy Exchanges in Europe, EEX facilitates a day-ahead market by the means of a uniform pricing auction[65]. On the day prior to delivery, price dependent and price independent hourly bids and offers can be submitted to the electronic EEX platform latest 12 p.m. Additionally, offers for individual power blocks consisting of at least two hours with the same quantity and price can be submitted. In accordance with the principle of the most executable volume, EEX clears all bids and offers and publishes hourly market clearing prices and volumes. In contrast to Electricity Pool Systems like the PJM Market it is not mandatory for energy consumers, producers and traders to participate in auctions at the exchange based system EEX. Liquidity on the EEX Intraday Market which covers the period between the EEX day-ahead auction and the actual delivery period on the next day is only fractional compared to the day-ahead auction. Real time imbalances in the power system are balanced by generation units which can provide positive or negative primary, secondary and tertiary reserve energy. TSOs procure reserve energy on separate markets[66].

In contrast to exchanged based trading, OTC trades take places directly between the counterparties and are often facilitated by broker companies. Transactions are executed via electronic broker platforms or bilaterally via telephone. Only standardised block contracts such as Base (delivery period h1-h24), Peak (h9-h20), Off-Peak (h1-h8, h21-h24), Night (h1-h6) and several others can be traded. Most day-ahead trading activities take place between 8 a.m. and 12 p.m. on the day prior to the delivery day. Thus, the continuous OTC market is important for market players to hedge larger volumes prior to the exchanged based auction at 12 p.m. The OTC-market can be considered to be the last forward market before the final EEX exchange clears. Although trades conducted on the electronic platforms can be seen by all market participants who have access to these platforms, there is to our knowledge no public register that publishes information about trading participants, trade prices or traded volumes on the OTC market. This certainly adds to the often criticised lack of transparency of OTC trading activities in comparison to exchange based trading. Therefore, the volumes traded on the day-ahead OTC market are difficult to quantify. However, the questioning of several market participants revealed that - in terms of volumes traded - exchange based and OTC based day ahead trading are in the same order of magnitude.

[65]See Grimm et al. (2008) for more EEX auction details.
[66]For more details see Swider and Weber (2007a).

A brief comparison between day-ahead EEX auction and day-ahead OTC prices for Base block contracts was published within the Energy Sector Inquiry by the European Commission (2007). The report states that *"As a result of continuous arbitrage, prices of identical products traded on different marketplaces (i.e. on power exchanges or OTC markets) develop in parallel. Indeed [. . .], prices for day-ahead baseload delivery observed on the EEX [. . .] and the German OTC market are very closely correlated both in terms of development and levels"*. This conclusion is imprecise, particularly in relation to the day-ahead Power Market. Firstly, continuous arbitrage is not possible as continuous OTC trading takes place in the morning hours before the EEX auction. Hence, there is a time gap between the two marketplaces. Secondly, since no data source is quoted it is not specified which type of price is meant by OTC price. Since OTC-trading is continuous, there is not one single price that could be used as a reference OTC price. More information regarding traded volumes, prices and a comprehensive overview was compiled by Rademaekers et al. (2008) on behalf of the European Commission.

There is a whole range of trading participants in the European and German Power Markets who can be broadly divided into generators and retailers with inherent physical long or short positions and pure traders and banks who typically aim to exploit prices differences and take speculative positions. However, the Energy Sector Inquiry by the European Commission (2007) states that large power producers are also engaged in speculative and arbitrage trading. Smaller producers and retailers on the other hand trade mainly to optimise their portfolios. Additionally, it is important to note that natural buyers do not necessarily buy and natural sellers do not necessarily sell on the day-ahead power market. Depending on their long-term procurement, hedging strategies and short term demand and supply variations, retailers might sell excess power and producers might repurchase power that was sold on future or forward markets in order to optimise their portfolios. Therefore, it is very likely that over time most market participants will appear on both sides of the market.

In early 2009, more than 150 participants from 18 European countries and the U.S. were registered to trade on the EEX day-ahead Power Market. They include all the major power utilities of Central Europe, transmission system operators, local energy companies and municipalities as well as pure energy trading companies, several banks and others. Small companies which do not have direct access to the EEX trading system can trade via separate accounts of other trading members. To our knowledge there are no sources stating how many of these trading participants are also active on the OTC market. However, due to the function of the OTC market to hedge positions before the EEX auction, we assume that most participants with considerable volumes are engaged in the OTC market as well. At the Energy Exchange Austria (EXAA), which we use as a snapshot of the OTC market[67], about 50 participants from 13 countries were registered. Although this number seems to be small in comparison to EEX, all major energy utilities of Central Europe as well as several banks and pure energy trading companies are trading members at EXAA.

2.3 Data

In order to facilitate a comparison of hourly EEX prices and OTC prices, we decided to use prices provided by EXAA as a snapshot of the OTC market. EXAA is an Austrian based power exchange which conducts an hourly day-ahead auction between 10.12 a.m. and 10.15 a.m. for two German and one Austrian delivery point. As there have been no congestions reported so far, prices at these delivery points were always identical on EXAA for the Austrian and German market areas. Additionally, it is crucial to mention that EXAA prices coincide with continuous OTC prices at the time of the auction, otherwise arbitrage between the two market places was possible. Several reasons favour EXAA data compared to OTC data. First and most important, EXAA provides hourly data which is crucial for our analysis, whereas only block products are traded on the OTC market. Second, the EXAA auction takes place at the same time every day, while trades on the continuous OTC market occur less regularly and there are periods of time with no trades at all. Last but not least, EXAA data is available for free and easy to access, whereas OTC data is costly and very difficult to obtain, if a set of all traded products and all active brokers is required. Hence, the data sets we use consist of hourly day-ahead data publicly provided by the EEX and EXAA on their internet platforms. They cover the period from October 1, 2005 to September 30, 2008. Accordingly, we work with a data set of 1,096 days including a price for each of the 24 hours for each delivery day. As there has been no trading on the weekends during the time period covered by our data, prices for delivery day Sunday and Monday were fixed on Fridays. The same principle holds for public holidays.

The average daily EEX price also known as Base contract is shown in Figure 2.1. The figure reveals two of the most apparent features of power prices: high volatility and price spikes. Table 2.1 and Table 2.2 list the hourly summary statistics for the EEX and EXAA respectively. Next to the mean, minimum, median and maximum price, the standard deviation and skewness for each hour is listed. The term h1 corresponds to the delivery period from 0-1 a.m. and so on. Additionally, the tables list summary statistics for five selected and frequently traded block products. A block product price consists of the average price of all hours it contains. All prices are quoted in €/MWh. Table

[67]See section 2.3 for more details.

2.1 reveals several basic features of the German Power Market. Firstly, mean prices in general follow the power demand curve. During night hours from h1-h6, power demand is at its lowest levels[68] with average prices at a range between 25 and 37 €/MWh. During the peak hours h9-h20 on the other hand, prices are on average more than twice as high. These higher prices are due to the fact that gas and oil fueled power stations produce at the margin most of the peak hours. These plants have higher variable generation costs than nuclear, lignite or coal fired power stations which generally produce at the margin during off-peak hours in the German system[69].

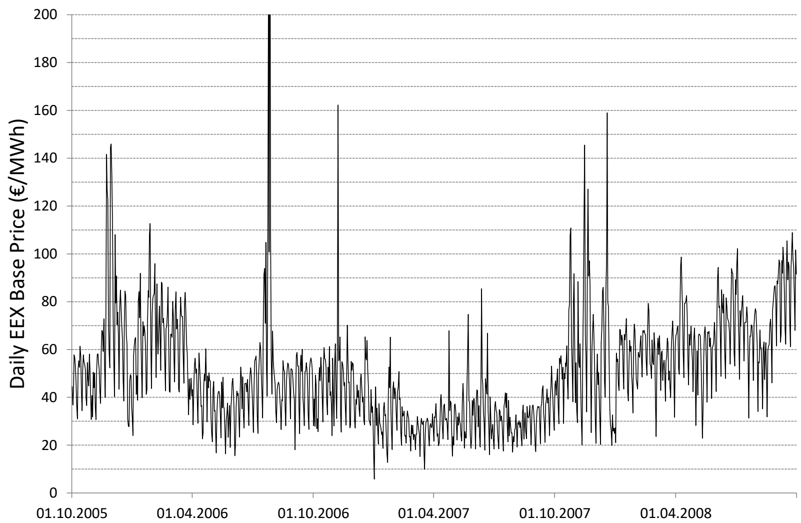


FIGURE 2.1: Daily EEX Base price. Data used with permission from EEX.

All hourly maximum power prices for h10-h16 in Table 2.1 originate from only two days in July 2006, a time when persistent high temperatures across Central Europe led to high power demand. Additionally, high river temperatures led to cooling water restrictions and reduced power output for a large number of power plants. The highest hourly maximum prices amounted to 2000.07 €/MWh for h12 on July 25, 2006 and 2436.63 €/MWh for h19 on November 11, 2006. Throughout this paper, we add alternative calculations excluding these two extreme price spikes, listed as 12a and 19a in Table 2.1. The minimum price of several night and morning hours within the timeframe observed was zero. Even if there was more supply than demand at a price of zero, power prices could not turn negative on EEX as the minimum price is set to be zero. Instead, the principle of pro rata assignment was adopted to match all bids and offers. Pro rata

[68] Compare to Figure 2.2.

[69] A detailed analysis of the German power plant structure is given by Borchert et al. (2006).

assignment refers to a proportionate execution of the offers at any given hour with supply surplus.

Hour	Mean	Min	Median	Max	Std. Dev.	Skewness
h1	36.89	1.64	34.28	76.02	14.11	0.52
h2	32.03	0.00	29.95	71.07	13.46	0.45
h3	28.65	0.00	27.12	67.93	12.88	0.39
h4	25.73	0.00	23.98	69.52	12.55	0.39
h5	26.06	0.00	24.05	69.92	12.43	0.38
h6	31.61	0.00	30.29	70.28	13.82	0.23
h7	36.63	0.00	34.80	94.51	19.89	0.18
h8	53.11	0.00	51.14	301.01	30.72	1.25
h9	59.44	0.00	55.70	437.26	33.45	2.34
h10	64.60	0.00	59.84	499.68	36.47	3.16
h11	68.54	0.00	62.68	998.24	44.65	9.08
h12	77.05	5.56	68.01	2000.07	81.64	16.12
h12a[b]	75.29	5.56	68.00	1399.99	57.33	12.22
h13	67.08	6.96	63.03	699.81	37.94	6.44
h14	63.57	2.65	59.17	699.88	37.12	6.30
h15	59.98	0.07	55.04	800.09	37.83	7.75
h16	56.04	0.12	51.56	693.23	34.21	6.79
h17	54.70	3.86	50.14	300.01	29.60	2.27
h18	61.84	6.90	54.07	821.90	49.03	7.10
h19	67.54	15.95	59.11	2436.63	86.50	19.85
h19a[c]	65.38	15.95	59.07	701.01	48.52	6.38
h20	60.00	17.97	57.06	250.04	27.75	1.78
h21	55.21	15.07	53.23	125.02	21.43	0.49
h22	48.61	13.48	46.31	105.93	17.92	0.49
h23	46.93	14.65	44.25	94.82	16.58	0.47
h24	38.23	1.61	35.28	80.98	14.22	0.58

Block period	Mean	Min	Median	Max	Std. Dev.	Skewness
h1-h24, Base	50.84	5.80	47.04	301.54	23.84	2.19
h9-h20, Peak	63.37	6.76	58.05	543.72	35.75	4.03
h1-h8, h21-h24[d]	38.32	4.85	36.95	83.19	14.85	0.47
h1-h6, Night	30.16	0.27	28.25	69.72	12.66	0.44
h17-h20, Noon	61.02	15.24	54.60	674.76	39.99	5.91

[a] Data used with permission from EEX, European Energy Exchange.
[b] excludes data from July 25th, 2006 (EEX h12: 2000.07 €/MWh)
[c] excludes data from November 7th, 2006 (EEX h19: 2436.63 €/MWh)
[d] Off-Peak

Table 2.1: Summary Statistics for Hourly and Block Day-Ahead EEX[a]-Prices.

Next to mean prices, also standard deviation and skewness of power prices are low during off-peak hours (h1-h8 and h21-h24) compared to peak hours. The most volatile hours in our data set are summer peak (h9 to h16) and winter peak hours (h18, h19). They exhibit standard deviations between 33.5 and 81.6 €/MWh. Standard deviations of h12 and h19 even exceed the average prices of these hours. Not surprisingly, their distribution is also highly right-skewed. Skewness ranges from 2.3 to 19.9 €/MWh. Off-peak hours on the other side display skewness of less than 0.6 €/MWh except of the ramping hour h8. Positive skewness of power spot prices is attributable to the convex shape of the power supply curve and to the fact that power is non-storable.

However, seasonal changes in price patterns are not observable from Table 2.1. While the highest prices during summertime are paid in h11-h13, prices peak in h18 and h19 during winter months. This originates from changing power demand patterns during the seasons as plotted in Figure 2.2. Demand peaks at noon during summer and in h18 and h19 during winter season, with absolute winter peak demand levels significantly higher than summer peaks. According to data provided by UCTE (2008), the 10 hours with the highest demand within the time period of our dataset can be found either in November or December, while lowest demand was measured in May and June. Additionally, weekly price patterns featuring lower prices on weekends and price changes caused by varying fuel prices are not apparent from Table 2.1.

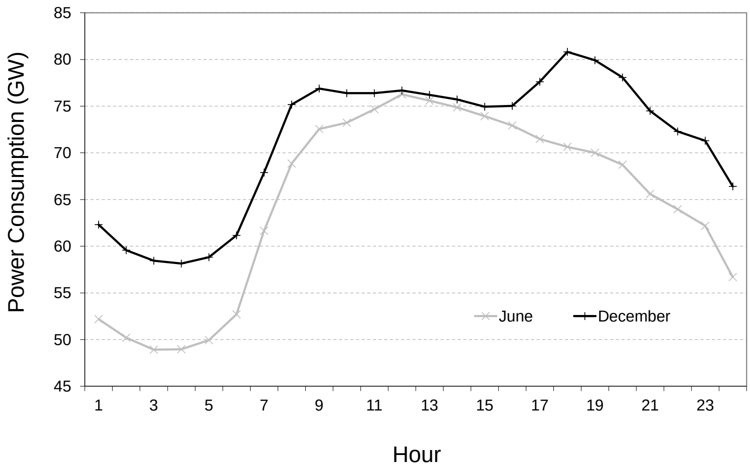


FIGURE 2.2: Power consumption in Germany on the third Wednesday in June and December 2007. Data provided by UCTE (2008)

Table 2.2 lists the summary statistics of EXAA prices, representing the continuous OTC market approximately 2 hours prior to the final exchange EEX. Regarding price shape, intraday variation and magnitude of mean prices, EXAA and EEX show very similar properties. However, standard variation, skewness and maximum prices display some remarkable differences. Standard variation is higher on EEX in all peak hours except of h20. Skewness is also higher on EEX for all peak hours. Additionally, maximum prices during the peak hours are uniformly lower on EXAA except of h20. The highest EXAA prices within the time period covered by our data were 888.00 €/MWh in comparison to 2000.07 €/MWh on EEX in h12 and 519.93 €/MWh in comparison to 2436.63 €/MWh in h19.

These differences support the thesis that power prices are more volatile and display more extreme variations at EEX, which - except for the illiquid intraday trading market - is considered to be the last opportunity for traders to close positions. EXAA and the OTC market, on the other hand, can be considered to be the last forward markets prior to EEX and thus they are less volatile and show less extreme variations. Datasets of the PJM Market comparing day-ahead and hour-ahead prices used by Longstaff and Wang (2004) and Douglas and Popova (2008) display very similar properties.

Hour	Mean	Min	Median	Max	Std. Dev.	Skewness
h1	36.97	6.83	35.00	81.00	13.38	0.51
h2	31.64	0.55	29.81	68.53	12.46	0.54
h3	28.17	0.01	26.40	65.64	11.84	0.53
h4	25.57	0.01	23.59	75.00	11.49	0.63
h5	26.00	0.01	24.15	62.50	11.56	0.53
h6	31.19	0.01	30.21	70.30	13.24	0.27
h7	37.14	0.01	36.58	92.06	18.62	0.21
h8	53.92	0.01	51.14	208.21	29.03	0.80
h9	59.81	0.01	57.53	205.00	29.52	0.82
h10	65.18	11.00	61.67	376.93	33.25	2.21
h11	69.26	11.67	65.00	459.46	35.88	2.82
h12	76.28	0.07	69.85	888.00	49.48	6.94
h13	67.63	20.60	63.97	458.89	33.86	3.78
h14	63.99	17.00	60.95	409.65	31.87	2.75
h15	60.16	3.51	57.07	350.00	30.85	2.41
h16	57.02	11.27	54.05	300.00	28.87	1.88
h17	56.65	9.83	52.06	240.00	28.97	1.49
h18	65.36	12.68	55.59	517.55	47.92	4.09
h19	68.31	17.60	60.00	519.93	46.63	3.87
h20	61.87	20.00	59.00	302.37	28.95	1.72
h21	55.78	19.40	54.94	127.78	20.69	0.49
h22	49.15	9.99	47.00	100.57	17.02	0.44
h23	48.10	1.00	45.73	90.00	16.47	0.36
h24	39.48	1.00	37.71	84.27	14.28	0.48

Block period	Mean	Min	Median	Max	Std. Dev.	Skewness
h1-h24, Base	51.44	13.60	48.40	177.85	22.32	1.15
h9-h20, Peak	64.29	17.26	60.25	299.99	32.03	1.89
h1-h8, h21-h24[b]	38.59	8.14	37.18	80.50	14.46	0.46
h1-h6, Night	29.92	1.40	28.25	66.25	11.95	0.50
h17-h20, Noon	63.05	16.52	56.52	370.41	36.47	2.81

[a] Data used with permission from EXAA, Energy Exchange Austria.
[b] Off-Peak

Table 2.2: Summary Statistics for Hourly Day-Ahead EXAA[a]-Prices

2.4 Realised Risk Premiums

As mentioned in section 2.1, standard cost-of-carry approaches cannot be applied to determine forward premiums in electricity markets due to the fact that power is non-storable in meaningful quantities at competitive cost. Hence, in equilibrium models the *"forward premium represents the equilibrium compensation for bearing the price and/or* *demand risk for the underlying commodity. [...]. Forward premia should be fundamentally related to economic risk and the willingness of different market participants to bear these risks."* (Longstaff and Wang, 2004). We define the risk premium[70] $RP_{i,t}$ as the difference between the expected spot price and the forward price for each hour i.

$$RP_{i,t} = F_{i,t} - E_t\left[S_{i,t+1}\right] \tag{2.1}$$

where $F_{i,t}$ is the forward price and $E_t\left[S_{i,t+1}\right]$ the conditional expectation of the spot price for hour i at time $t+1$. The expectation is conditional to all information available at time t. There are basically two ways to analyse risk premiums, the ex post and the ex ante approach. The ex post approach - employed in this section - uses only realised spot data. The ex ante approach - employed in section 2.5 - requires a model to estimate spot prices. Analysing realised risk premiums necessitates some additional assumptions. We denote the difference between the expected and the realised spot price as forecast error which can also be written as random noise $\epsilon_{i,t+1}$ (equation 2.2). In the course of this section, we assume that the forecast error $\epsilon_{i,t+1}$ has a mean of zero and is independent of information available at time t.

$$\epsilon_{i,t+1} = E_t\left[S_{i,t+1}\right] - S_{i,t+1} \tag{2.2}$$

We define EEX as the spot market and EXAA as forward market using the data presented in the previous section. Hence, the timeframe between t and $t+1$ is only two hours. Thus, the realised premium rRP_i is on average positive if the price at the forward market EXAA is higher than at the spot market EEX and vice versa.

$$rRP_i = \frac{1}{T}\sum_{t=1}^{T} EXAA_{i,t} - EEX_{i,t+1} \tag{2.3}$$

Risk premiums of block contracts are computed in the same way. We use t-statistics to ascertain not only whether the premiums observed are positive or negative, but also to test whether the null-hypothesis that rRP_i is zero can be rejected or not. Autocorrelation and heteroscedasticity consistent Newey-West estimates of the variances were used for all t-statistics.

Table 2.3 and Figure 2.3 summarise the mean hourly risk premiums paid in the German day-ahead Power Market for all 1096 days of the dataset. The overall mean of

[70] As both terms forward premium and risk premium are used in literature to describe the same concept, we use these terms interchangeable.

the premium represented by the Base block contract is positive (0.61 €/MWh), but not statistically different from zero. However, premiums observed are statistically significant at the 5 percent level for 5 of the 24 hourly contracts. Significant positive premiums can be observed exclusively for evening hours. Three of the four hours with the highest demand levels in winter h17-h20[71] were traded with positive premiums that are significantly different from zero at the 5 percent level. The highest premium were paid in h18 (3.52 €/MWh) and h17 (1.95 €/MWh). In terms of the average EEX price in h18, the premium accounts for a percentage premium of 5.9 percent. Additionally, the frequently traded block h17-h20 displays a positive premium of 2.03 €/MWh, statistically significant at the 10 percent level.

	All Days		Weekdays		Weekends	
Hour	**Mean**	**t-statistic**	**Mean**	**t-statistic**	**Mean**	**t-statistic**
h1	0.08	0.28	0.42	1.24	-0.74	-1.47
h2	-0.39	-1.36	-0.13	-0.50	-1.04	-1.74 *
h3	-0.48	-1.49	-0.09	-0.30	-1.46	-2.41 **
h4	-0.16	-0.39	0.37	0.79	-1.49	-2.18 **
h5	-0.07	-0.19	0.32	0.84	-1.02	-1.60
h6	-0.42	-1.15	-0.21	-0.58	-0.94	-1.48
h7	0.52	1.04	0.09	0.15	1.58	1.73 *
h8	0.81	0.88	0.24	0.21	2.22	3.04 ***
h9	0.36	0.41	0.17	0.15	0.86	1.51
h10	0.58	0.60	0.61	0.53	0.50	0.73
h11	0.72	0.67	0.81	0.53	0.50	0.68
h12	-0.77	-0.22	-1.27	-0.26	0.47	0.54
h12a[a]	0.72	0.85	0.82	0.73		
h13	0.55	0.56	0.83	0.62	-0.16	-0.26
h14	0.42	0.42	0.35	0.26	0.59	0.99
h15	0.17	0.15	0.00	0.00	0.62	1.47
h16	0.97	0.97	0.93	0.71	1.07	2.07 **
h17	1.95	1.98 **	2.29	1.66 *	1.10	1.98 **
h18	3.52	2.61 ***	4.49	2.15 **	1.10	1.17
h19	0.77	0.18	0.90	0.15	0.46	0.55
h19a[b]	2.88	1.55	3.86	1.25		
h20	1.87	3.26 ***	2.68	3.79 ***	-0.14	-0.18
h21	0.58	1.15	0.32	0.60	1.20	1.42
h22	0.53	1.14	0.42	0.84	0.82	1.21
h23	1.17	2.14 **	1.29	2.58 ***	0.86	1.12
h24	1.25	2.59 ***	1.27	2.63 ***	1.21	1.70 *

Block period	**Mean**	**t-statistic**	**Mean**	**t-statistic**	**Mean**	**t-statistic**
h1-h24, Base	0.61	1.27	0.71	1.41	0.34	1.30
h9-h20, Peak	0.93	1.12	1.07	0.96	0.58	1.23
h1-h8, h21-h24[c]	0.27	1.04	0.36	1.26	0.06	0.22
h1-h6, Night	-0.24	-0.92	0.11	0.44	-1.11	-2.31 **
h17-h20, Evening	2.03	1.75 *	2.59	1.55	0.63	1.04

t-statistics are based on autocorrelation and heteroskedasticity consistent estimates of the variances
*, **, *** denote statistical significance at the 10%, 5% and 1% levels, respectively
[a] excludes data from July 25th, 2006 (EEX: 2000.07 €/MWh, EXAA: 364.92 €/MWh)
[b] excludes data from November 7th, 2006 (EEX: 2436.63 €/MWh, EXAA: 126.48 €/MWh)
[c] Off-Peak

Table 2.3: Tests for the Presence of Risk Premiums in the German Power Spot Market.

[71] Compare to Figure 2.2.

Additionally, we analyse subsets of the data in order to obtain a more detailed pattern of time and seasonal variations of the risk premiums observed. As shown in Table 2.3, the subsets "weekdays" (782 sample days) and "weekend days" (314 sample days) are drawn from the overall sample. Their comparison reveals some remarkable differences. First, positive risk premiums for the evening peak hours are much smaller and not significant on weekend days. By contrast, the same hours during weekdays display risk premiums that are significantly different from zero. The highest positive premiums were paid in h18 (4.49 €/MWh) and h20 (2.68 €/MWh). In terms of the average EEX prices on weekdays, the positive premium paid on EXAA accounts for a percentage premium of 6.4 percent in h18 and 4.1 percent in h20. The comparison of the night hours h1-h6 uncovers additional information about varying premiums. While risk premiums are close to zero and not statistically significant on weekdays, they are negative on weekend days. Risk premiums are negative at a 10 percent confidence level for three of the six night hours. The highest negative premiums were paid in h3 (-1.46 €/MWh) and h4 (-1.49 €/MWh). In terms of the average EEX prices on weekend days, the negative premium accounts for a percentage premium of -5.2 percent in h3 and -6.0 percent for h4. Also the frequently traded night block h1-h6 displays a negative premium (-1.11 €/MWh) on weekend days, statistically significant at the 5 percent level.

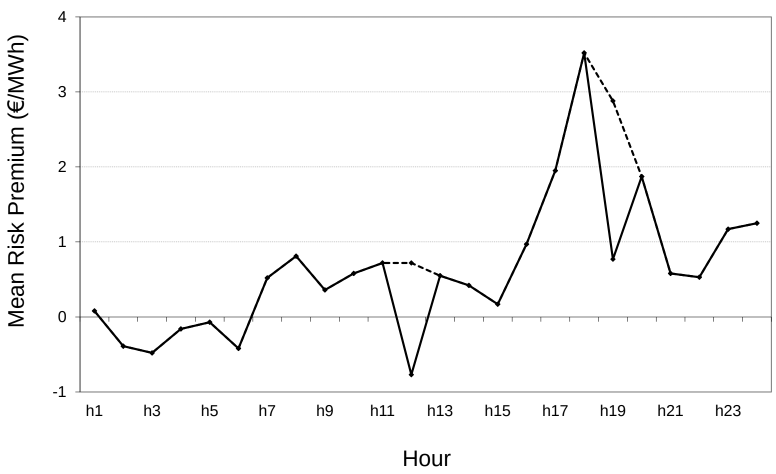


FIGURE 2.3: Hourly mean risk premium, dotted line represents h12a and h19a from table 2.3.

Next, the dataset was further divided into summer and winter month in order to look for seasonal variations of the risk premiums. We define May to August as summer (369 sample days) and November to February as winter month (361 sample days). As shown in Table 2.4, we focus on the evening peak hours that displayed positive risk premiums in the overall sample. Comparing all summer and all winter days reveals clear differences in the premiums paid. The average risk premium of the four hours is more than eight times higher during winter months in comparison to summer months. Premiums in summer month are all smaller than 1 €/MWh and none is statistically significant. Interestingly though, merely the risk premiums for h17 (4.66 €/MWh) and h20 (4.27 €/MWh) are statistically significant at a 5 percent level during winter time. Although h18 and h19a display even larger mean premiums, they are not significant due to their large autocorrelation and heteroscedasticity consistent estimated volatilities. As shown in Table 2.4, this changes if one further divides the winter days into weekdays (259 sample days) and weekend days (102 sample days). Again, risk premiums are higher on weekdays than on weekend days. Additionally, premiums are statistically significant at a 10 percent level for three of the four hours on weekdays, but for none of the hours on weekend days. Apart from h19a, the highest premiums were paid in h17 (5.83 €/MWh) and h18 (9.96 €/MWh) during the winter period. In terms of the average EEX prices for h17 and h18 on winter weekdays, these premiums account for percentage premiums of 8.1 and 10.2 percent, respectively. All results in this section are subject to the restriction that other fundamentals than seasonal patterns (such as wind power, power plant availability) were not included. However, they are included in the ex ante model presented in section 2.5.

	All Days		Weekdays		Weekends	
Hour	**Mean**	**t-statistic**	**Mean**	**t-statistic**	**Mean**	**t-statistic**
h17 May - Aug	-0.15	-0.07				
h18 May - Aug	0.65	1.04				
h19 May - Aug	0.47	0.85				
h20 May - Aug	0.95	1.58				
h17 Nov - Feb	4.66	2.80 ***	5.83	2.51 **	1.69	1.27
h18 Nov - Feb	7.46	1.48	9.96	1.83 *	1.12	0.56
h19 Nov - Feb	0.11	0.01	-0.20	-0.01	0.88	0.60
h19a[a] Nov - Feb	6.52	1.26	8.75	1.08		
h20 Nov - Feb	4.27	3.23 ***	5.68	3.96 ***	0.69	0.39

t-statistics are based on autocorrelation and heteroskedasticity consistent estimates of the variances

*, **, *** denote statistical significance at the 10%, 5% and 1% levels, respectively

[a] excludes data from November 7th, 2006 (EEX: 2436.63 €/MWh, EXAA: 126.48 €/MWh)

Table 2.4: Tests for Time Variation of Risk Premiums during Winter and Summer.

2.5 Measurements of Risk

Having found significant positive and negative forward premiums for hourly contracts, we now analyse how they relate to measurements of risk - the second and the third moment of spot prices. Using equation 2.1 and rearranging the equilibrium equation by

Bessembinder and Lemmon (2002), the risk premium shall be related to the variance and skewness of spot prices (equation 2.4).

$$RP_{i,t} = \alpha Var\left(S_{i,t+1}\right) + \beta Skew\left(S_{i,t+1}\right) \tag{2.4}$$

The following procedure has been applied to verify the link between ex ante risk premiums $eaRP_{i,t}$ and the measurements of risk (equation 2.5). First, an estimator of the expected spot price $\hat{E}\left[S_{i,t+1}\right]$ is developed. Second, estimators for both, the expected variance $\hat{V}ar\left(S_{i,t+1}\right)$ and expected skewness $\hat{S}kew\left(S_{i,t+1}\right)$ need to be obtained. Finally, we regress the ex ante premium on the ex ante estimators of the variance and skewness.

$$eaRP_{i,t} = ln\left(\frac{\hat{E}_t\left[S_{i,t+1}\right]}{F_{i,t}}\right) = \alpha\hat{V}ar\left[S_{i,t+1}\right] + \beta\hat{S}kew\left[S_{i,t+1}\right] \tag{2.5}$$

An ARMA(1,1)-GARCH(1,1) time-series model is employed to obtain estimators for the expected spot price and its expected variance. Similar approaches have recently been applied by Garcia et al. (2005) and Swider and Weber (2007b). All calculations have been performed using R (R Development Core Team, 2009) and the R package fGarch (Wuertz and Chalabi, 2009). Using price data of working days only and readjusting for intra-weekly patterns, separate ARMA(1,1)-GARCH(1,1) runs have been deployed for each of the 24 hourly contracts. The mean absolute percentage error (MAPE) of the ARMA(1,1)-GARCH(1,1) model varies from 11.2 to 82.6 percent for the hourly contracts. However, it needs to be mentioned that a very high MAPE of four night hours h2-h5 (31.6 to 82.6 percent) is due to few prices close to zero that cause very large single absolute percentage errors. The average MAPE across all hours except h2-h5 amounts to 15.1 percent. Thus it is slightly higher than a MAPE of 13.0 percent obtained by Swider and Weber (2007b) for the German Day-Ahead Market. This might be due to the fact that Swider and Weber use a different set of EEX data (from 2002 to 2004) and daily average prices in contrast to hourly prices in this study.

Additional to the ARMA(1,1)-GARCH(1,1) model, a tightness factor ($TF_{i,t}$) - based on fundamental supply and demand data - is introduced to provide a conditional estimate of the skewness. $TF_{i,t}$ is used to measure the tightness of the power system. $TF_{i,t}$ close to or above one indicates a tight system, in which expensive peak load plants are more likely to be required to meet demand and therefore the probability of price spikes and right skewed prices increases. Thus, $TF_{i,t}$ provides a conditional estimate of the expected price skewness. The expected power demand is divided by the expected power supply for each hour to obtain $TF_{i,t}$.

$$TF_{i,t} = \frac{E_t\left[D_{i,t+1}\right]}{E_t\left[S_{EEX,i,t+1}\right] + E_t\left[S_{Wind,i,t+1}\right]} \tag{2.6}$$

Were $E_t\left[D_{i,t+1}\right]$ is the expected power demand for each hour i, $E_t\left[S_{EEX,i,t+1}\right]$ the expected power plant availability reported by EEX and $E_t\left[S_{Wind,i,t+1}\right]$ the expected wind power production. EEX publishes power plant availability figures for the next day each working day by 10 a.m. Although reporting to EEX is not mandatory for producers, availability figures for most nuclear, lignite, coal, gas and oil fired plants as well as expected hydro production are published by EEX on an aggregated level. Hence, the EEX availability report provides the best information available even if it is not complete. However, EEX does not report the expected wind power production for the next day. Since the installed capacity of wind turbines in Germany amounted to nearly 24 GW (BWE, 2009) by the end of 2008, feed-in from wind production has a significant impact on both, the supply and demand ratio as well as power prices[72]. Publicly available day-ahead wind production forecast data published by the four German TSOs 50Herz, Amprion, ENBW and Transpower have been added up to obtain the total level of expected wind production in Germany. Since there is no demand forecast publicly available, we adopted an ARMA(1,1) approach to forecast the expected load for each hour i while using only working days (no weekend day, no holidays, no bridging days) and readjusting for intra weekly demand patterns. The MAPE of the ARMA(1,1) model varies from 2.3 to 5.3 percent for the hourly demand forecasts, the average MAPE across all hours amounts to 3.3 percent.

Given the estimators of spot prices, its variation and the tightness factor obtained above, we now estimate the following regression.

$$eaRP_{i,t} = ln\left(\frac{\hat{E}_t\left[S_{i,t+1}\right]}{F_{i,t}}\right) = \gamma + \alpha\hat{V}ar\left[S_{i,t+1}\right] + \beta TF_{i,t} + \epsilon_{i,t} \tag{2.7}$$

Regression results of the estimated variance and the tightness factor on the ex ante percentage risk premium are shown in Table 2.5. Only summary statistics of working days are listed, starting from the 12th of April 2006 (607 days in total) as EEX availability figures were not published before that date. A very strong positive correlation - ranging from 0.9 to 2.9 - between the ex ante percentage premiums and the tightness factors is apparent from Table 2.5, β is significant for all hours at the 1 percent level. Simultaneously, the intercept γ is strictly negative - ranging from -0.8 to -2.1 - and significant at the 1 percent level in all hours. Other things being equal, this translates into negative risk premiums for low tightness factors and positive premiums for tightness factors close

[72] See Sensfuß et al. (2008) and Wissen and Nicolosi (2007) for more details on the merit-order effect.

to one that coincide with a high estimated skewness. Remarkably, the off-peak hours h3-h5 with the lowest load levels display the highest levels for β and the lowest levels for the intercept γ, this is due to strongly negative risk premiums paid for very low tightness factors. Regression results of the estimated variance are less clear. While α is positive in all off-peak hours and significant at the 1 percent level for 11 off-peak hours, α is negative for 10 out of 12 peak hours, but significant at the 1 percent level for only 4 peak hours.

	Estimate			t-statistic		
Hour	γ	α	β	γ	α	β
h1	-1.10	0.38	1.49	-15.06 ***	7.86 ***	14.55 ***
h2	-1.48	0.27	2.09	-17.71 ***	15.71 ***	16.84 ***
h3	-1.82	0.37	2.60	-18.70 ***	11.47 ***	17.69 ***
h4	-2.09	0.30	2.94	-19.04 ***	17.15 ***	18.06 ***
h5	-1.91	0.44	2.61	-18.52 ***	13.08 ***	17.47 ***
h6	-1.38	0.40	1.81	-15.15 ***	8.52 ***	14.45 ***
h7	-0.91	0.44	1.02	-9.51 ***	7.56 ***	8.79 ***
h8	-0.86	0.38	0.87	-8.96 ***	7.26 ***	8.26 ***
h9	-0.93	-0.11	1.03	-10.58 ***	-1.77 *	11.34 ***
h10	-0.99	-0.07	1.09	-11.27 ***	-1.11	11.83 ***
h11	-0.99	-0.17	1.11	-11.35 ***	-3.19 ***	12.16 ***
h12	-1.13	-0.18	1.23	-12.30 ***	-4.32 ***	12.89 ***
h13	-1.09	-0.16	1.21	-13.51 ***	-2.75 ***	14.26 ***
h14	-1.13	-0.12	1.26	-13.64 ***	-2.21 **	14.26 ***
h15	-1.14	-0.16	1.30	-13.33 ***	-2.84 ***	14.07 ***
h16	-1.24	-0.10	1.41	-14.09 ***	-1.64	14.75 ***
h17	-1.24	-0.04	1.43	-13.07 ***	-0.55	13.59 ***
h18	-1.52	0.06	1.72	-16.42 ***	1.00	16.52 ***
h19	-1.57	-0.02	1.76	-15.80 ***	-0.63	16.02 ***
h20	-1.09	0.31	1.18	-13.84 ***	3.36 ***	13.68 ***
h21	-0.87	0.21	0.96	-13.62 ***	2.18 **	13.60 ***
h22	-0.78	0.27	0.88	-11.79 ***	3.41 ***	11.61 ***
h23	-0.84	0.47	0.97	-11.49 ***	4.82 ***	11.14 ***
h24	-0.92	0.35	1.20	-11.26 ***	5.00 ***	11.03 ***

*, **, *** denote statistical significance at the 10%, 5% and 1% levels, respectively
A sensitivity analysis of wind input data is available on request

Table 2.5: Regression of ex ante risk premiums on estimators of measurements of risk (equation 2.7)

The results presented here coincide with those presented in section 2.4. All other things being equal, high demand levels lead to a high tightness factor resulting in positive risk premiums akin to the ex post analysis, which also shows positive premiums for hours with the highest demand levels (see Table 2.4). However, the ex ante analysis provides an additional layer of information, as power plant availabilities and wind power production forecasts are included. Therefore, the tightness factor includes not only seasonal patterns (demand, planned long term power plant outages) but also short term changes on the supply side (wind, short term power plant outages). The most significant day-to-day variations of the tightness factors stem from changes in wind power. Other thing being equal, high wind production in high demand hours is reducing the tightness factor and decreases or eliminates positive premiums, whereas high wind production in low demand hours further increases negative premiums.

2.6 Interpretation

The results obtained in section 2.4 and 2.5 are broadly consistent with the equilibrium model for power markets developed by Bessembinder and Lemmon (2002) and the empirical analysis of PJM market prices undertaken by Longstaff and Wang (2004). The model developed by Bessembinder and Lemmon associates the variance and skewness of the underlying power prices to the premiums paid in the forward market. Our data confirm that power traders are willing to pay large premiums of up to 10 percent for the evening peak hours h17-h20 on weekdays during winter months. These hours feature the highest demand levels of the year and price spikes often occur. However, traders are not willing to pay risk premiums for the same hours on weekends or during summer season when demand is much lower. Seasonality of risk premiums was also shown by Pirrong and Jermakyan (2008) and Lucia and Torró (2008). Additionally, we found that risk premiums are positively related to the tightness factor which was used as a measurement of risk giving an indication of the estimated skewness. Other things equal, the analysis shows that positive premiums were paid in hours in which the system was expected to be tight and vice versa.

The fact that the prices of two hours during the timeframe observed were above 2,000 €/MWh clearly demonstrates that the risk of price spikes is real. In a similar fashion to Benth et al. (2008) one can use the term "sellers market" to explain the presence of positive risk premiums for hours with the highest demand and tightness factors close to or above one. The data confirm that power traders behave risk-aversely and rationally and are willing to pay significant risk premiums in the presence of risk factors. This is rational, as the right skewness of power prices can lead to substantial losses for those who hold short power forward positions. Pirrong and Jermakyan (2008) denote this as left skewness of the profit distribution for those who are short. They describe the case of a large utility in the U.S. whose entire year's earnings were wiped out on one single day due to a short position. Cases of corporate default and near bankruptcy due to power price spikes were also reported by Bessembinder and Lemmon (2002). It is well understood that there is a demand for risk reduction and companies profit from reducing risk of their cash flows and variability of returns by hedging their positions[73].

On the other side, there is only little skewness during off-peak hours, particularly from h1 to h6 when demand is at its lowest level. Hence, Bessembinder and Lemmon argue

[73]See e.g. Smith and Stulz (1985) for more information on corporate hedging strategies.

that sellers who want to hedge their revenues induce a downward bias in equilibrium forward prices. The absence of buying interest during hours of lowest consumption leads to a “buyers market” with negative risk premiums. Our findings confirm this theory. Statistically significant negative premiums of up to -6 percent were paid for several night hours and the night block h1-h6 on weekend days. These periods of time coincide with the lowest load levels of each week. The ex ante analysis in section 2.5 confirms these results as night hours with low tightness factors display on average negative premiums.

However, it is not feasible to compare the order of magnitude of the premiums observed in the German and the PJM Market. This is due to the different type of data sets that were used. While we compare two different types of hourly day-ahead prices, Longstaff and Wang (2004) use a set of day-ahead and hour-ahead data. Nevertheless, positive as well as negative risk premiums for some individual hours seem to be large in comparison to other studies as the timeframe between the forward and the spot market is less than two hours. According to Bessembinder and Lemmon (2002) and Hadsell and Shawky (2007), the existence of large premiums could be an indication that the German Power Spot Market is not yet fully integrated into the wider financial market, despite the fact that several pure trading companies and investment banks are active in it.

2.7 Conclusion

This paper presents an empirical analysis of risk premiums paid in the German day-ahead Power Market. We find negative as well as positive risk premiums that are significantly different from zero for hourly delivery contracts. Additionally, the ex ante analysis shows that risk premiums are directly related to the tightness of the system. Our results are consistent with equilibrium forward pricing models and empirical results by Bessembinder and Lemmon (2002), Longstaff and Wang (2004) and Pirrong and Jermakyan (2008) for the PJM Market and confirm that energy traders behave rationally like risk averse-agents. It remains to be seen how the introduction of negative prices will affect negative risk premiums of weekend night hours in the future. From September 2008 EEX reduced the price floor, negative prices of up to -3,000 €/MWh are now possible. Negative prices might result in a left-skewed price distribution and larger negative premiums for the hours affected.

Our dataset covers a period of only three years which does not allow for an analysis of how the entrance of new market participants affected the market. Hence, we are not looking into whether systematic changes in risk premiums have occurred over time. As trading volumes increased and neutral pure trading companies and banks started in the power trading businesses during recent years, one would expect risk premiums to decrease over time[74]. Additionally, the data used did not allow for an investigation of how prices of the continuous OTC market react to new information within a trading day. This could be an interesting subject for further research.

We explicitly do not analyse whether risk premiums are paid on the EEX day-ahead Market in comparison to the Intraday Market which covers the time frame between the day-ahead auction and the actual delivery period. This could be an interesting subject for further research as soon as market liquidity improves and data problems are solved. Unlike Daskalakis and Markellos (2009), we argue that the EEX intraday data are not of satisfactory quality to conduct further research on risk premiums for several reasons. First, since intraday trading has started in September 2006, there have been no intraday trades reported in 45 percent of the hours in 2006, 19 percent of all hours in 2007 and 3 percent of all hours in 2008 resulting in missing price data. Secondly, the estimated figure of hours with only one trade is in the same order of magnitude in each year[75]. Additionally, it is hardly feasible to compare the prices of the EEX day-ahead Auction with prices of the continuous EEX Intraday Market. EEX publishes the minimum, maximum, average and last intraday price of each hour. As it is not known at what specific time intraday trades take place and the trading period can be longer than 24 hours, the determination and comparison of risk premiums between the day-ahead auction and the continuous intraday market is not consistent.

[74] See Bessembinder and Lemmon (2002) and Hadsell and Shawky (2007).

[75] Estimated percentage of intraday hours with only one trade: 20 percent in 2006, 17 percent in 2007 and 6 percent in 2008.

The Value of Information in Explicit Cross-Border Capacity Auction Regimes in Electricity Markets

This chapter is based on Richter and Viehmann (2014)[76]. This paper is joined work with my co-author Jan Richter.

Abstract

We study two electricity markets connected by a fixed amount of cross-border capacity. The total amount of capacity is known to all electricity traders and allocated via an auction. The capacity allocated to each bidder in the auction remains private information. We assume that traders are faced with a demand function reflecting the relationship between electricity transmitted between the markets and the spot price difference. Therefore, traders act like Bayesian-Cournot oligopolists in exercising their transmission rights when presented with incomplete information about the competitors' capacities. Our analysis breaks down the welfare effect into three different components: Cournot behavior, capacity constraints, and incomplete information. We find that social welfare increases with the level of information with which traders are endowed.

[76]Available here: https://doi.org/10.1016/j.enpol.2014.03.023.

3.1 Introduction

Efforts to liberalize European electricity markets led to unparalleled structural changes within the last 10 to 15 years. Directives and regulations issued by the European Commission aimed to open markets, ensure non-discriminatory third-party access to power grids[77] and enforce cross-border trading activities[78] in order to harmonize prices and to mitigate market power. Resulting from Article 6 of Regulation 1228/2003 –*"Network congestion problems shall be addressed with non-discriminatory market based solutions which give efficient economic signals [...]"*–, non-market-based congestion methods such as *first-come-first-serve* or *pro-rata* were replaced by market-based regimes like *implicit* and *explicit* auctions. In *explicit* auction regimes, the right to use cross-border capacity is sold first stage to market participants by a uniform-pricing auction. In a second stage, market participants then have to decide which share of their transmission rights to exercise in order to schedule a power flow from one market area to another.

Explicit auctions have been criticized mainly for two reasons. First, they might allow for exertion of market power. A firm might acquire capacity to block it or strategically misuse it to protect a dominant position in one regional market. Second, firms face incomplete information with respect to the demand for power transmission. Traders might just not know ex ante in which region excess demand (and therefore prices) are larger and might nominate capacity in the wrong direction. However, explicit auctions are still in place at many interconnectors.[79]

We add to the analysis of explicit auctions an additional source of inefficiency, namely the inefficiency arising from strategic usage of capacity under incomplete information with respect to the allocation of capacity among competing traders. To do so, we consider explicit auction regimes as two stage games: while transmission rights are sold to firms via an auction in the first step and auction results are made public, the actual utilization of transmission capacity is determined by firms in the second step, in which firms essentially play a Bayesian-Cournot game. The strategic variable is a firm's utilization of transmission rights. We solely focus on the second stage of the game and argue why this is sufficient to demonstrate the inefficiency of the auction regime.

Since the total cross-border capacity is fixed, there is a strong stochastic dependency structure between the firms' transmission rights. Consequently, equilibrium strategies can not be derived analytically. Therefore, we solve the model numerically for the case of three firms, which is the simplest relevant model specification – in the case of two

[77] European Union, Directive 54/EC (2003).

[78] European Union, Regulation EC No 1228 (2003).

[79] Examples are, among others, the interconnectors between France and the UK, France and Italy, Germany and Switzerland and Czech Republic and Poland.

firms, the game is subject to complete information because total capacity is common knowledge.

It turns out that a unique equilibrium exists, provided that firms are symmetric. In particular, the equilibrium itself must be symmetric. This is achieved by showing that the best response function converges to a unique fixed point – as opposed to the standard form Cournot oligopoly, in which the best response function only converges as long as $n < 3$. This result enables us to implement a stable algorithm that converges to the unique symmetric Bayesian-Cournot equilibrium.

The simulation results show that in the unique Bayesian-Cournot equilibrium, firms fully exercise their transmission rights up to a certain threshold. When the transmission rights with which a firm is endowed exceed this threshold, a bend occurs, leaving afterwards the strategy increasing in a convex manner up to the firm's monopoly output.

Moreover, social welfare increases with the level of information. The increase in social welfare is driven by an increase in producer surplus – i.e., when firms have more information, they can coordinate better on total electricity transmission. In particular, firms have an incentive to commit on an industry-wide information sharing agreement *ex-ante*. Stabilizing total transmission reduces its variance, which in turn lowers consumer surplus. However, the effect on consumer surplus is small and can be ambiguous, depending on the model parameters.

The remainder of this paper is structured as follows. In Section 3.2, we provide a literature review. In Section 3.3, we explain cross-border economics, auction offices and further motivate the model. The model and analytical results are presented in Section 3.4. The results of the numerical solution are presented and discussed in Section 3.5. Finally, Section 3.6 concludes.

3.2 Related Literature

The inefficiency of explicit auction regimes is unchallenged and has been documented in recent studies. Meeus (2011a) describes the transition from explicit to implicit market coupling of the so-called *Kontek*-cable connecting Germany and the Danish island Zealand. He shows that implicit price coupling clearly outperforms explicit auctions. Gebhardt and Höffler (2013) find that cross-border capacity prices (first stage of the two-stage game) at the German-Danish and German-Dutch borders predict on average spot price differentials correctly, but with a lot of noise. Similar arguments are provided by Dieckmann (2008) and Zachmann (2008) who show that uncertainty about spot prices and timing of explicit auction regimes lead to a poor performance. For the

German power market, Viehmann (2011) empirically shows the high volatility of spot prices also in comparison to their expected values.

While some of the literature mentioned above identifies market abuse as one possible reason for the inefficiencies observed, Bunn and Zachmann (2010) analytically derive cases in which dominant players, such as national incumbents, can maximize their profits by deliberately misusing cross-border capacities. The authors then analyze empirical data from the *IFA*-interconnector between France and UK and disclose flows against price differentials as well as unused capacity in the profitable direction in a significant number of hours. Additionally, Bunn and Zachmann (2010) provide a list of various design deficiencies contributing to the poor performance of explicit auction regimes. Finally, Turvey (2006) provides a broad overview about non-market and market-based congestion management methods and detailed information about South Eastern European markets.

The issue of incomplete information with respect to production capacities in Cournot oligopolies has recently been discussed by Richter (2013), who provides a characterization of equilibrium strategies when a firm's capacities are stochastically independent. Moreover, sufficient conditions for the existence and uniqueness of a Bayesian-Cournot equilibrium are given. Bounded capacity is modeled by curtailing the firm's strategy space. We adopt this approach, since it ensures that the strategy spaces are compact and the expected payoff function is concave given a linear demand function, ensuring the existence of an equilibrium by Nash's theorem.

Regarding the issue of information sharing in oligopolies, literature focuses on Bayesian Cournot models in which there are no non-negativity constraints and no capacity constraints with respect to outputs. Provided the common prior belief is normally distributed, equilibrium strategies are linear (or affine) and closed-form solutions can be derived. An overview of these models is provided by Raith (1996). In all such models, firms face uncertainty with respect to marginal costs, or inverse demand, or both.

Most similar to the setting discussed in the paper at hand is the case of unknown costs, since costs as well as capacities are private values in which equilibrium strategies should be monotonous. Shapiro (1986) finds that in this case, firms have an incentive to share information, meaning that sharing information increases expected producer surplus. Moreover, he finds that consumer surplus decreases, whereas social welfare increases as a result of a positive net effect.

As outlined in the previous section, we obtain similar results as Shapiro, although the impact on consumer surplus is not that clear in the model developed. This is due to non-negativity and capacity constraints on outputs, leading to equilibrium strategies that are not affine. Thus, well-known results regarding information sharing can be reversed by introducing constraints – an issue that was addressed earlier by Maleug and Tsutsui (1998) and recently by Richter (2013).

3.3 Power Interconnectors

To further justify the use of the Cournot approach, we provide insights into interconnector economics and briefly introduce European auction offices and their information policies.

3.3.1 Interconnector Economics

While pools like the *PJM Market* in the US deal with regional supply and demand imbalances via nodal pricing, the predominant system in Europe can be described as a connection of market areas. In most cases, market areas that are connected by power interconnectors are equivalent to national borders.[80]

Today, the two prevailing mechanisms to allocate scarce cross-border capacities in Europe are *implicit* and *explicit* capacity auctions. With *implicit* auctions, also referred to as *market coupling* or *market splitting*, the auctioning of transmission capacity is implicitly integrated into the day-ahead exchange auctions of the connected market areas. Power exchanges can ensure welfare-maximizing cross-border flows between the market areas as they possess full information about all hourly supply and demand curves in the connected market areas and the available cross-border capacity.

When explicit capacity auctions are in place, the right to use cross-border capacity is sold in a first stage to market participants by a uniform-pricing auction, usually on a yearly, monthly and daily basis. In daily auctions, firms can bid for each hour of transmission capacity separately. In a second stage, market participants have to decide which share of their transmission rights to exercise in order to schedule a power flow from one market area to another.[81]

The basic interconnector economics are pictured in Figure 3.1, in which the relation between the *used transmission capacity* Q and the price spread P between two market areas is shown. When no transmission capacity is utilized ($Q = 0$), the price spread is at its maximum. The more capacity is booked to flow power from the low price area to the high price area, the smaller the price spread becomes. When the total available cross-border capacity $\hat{t}$ is not sufficient to equalize prices (pictured left), total welfare is

[80] Exceptions are Italy, the United Kingdom and the Scandinavian countries.

[81] A comprehensive overview of explicit and implicit cross border auctions is given by Kristiansen (2007) and Jullien et al. (2012).

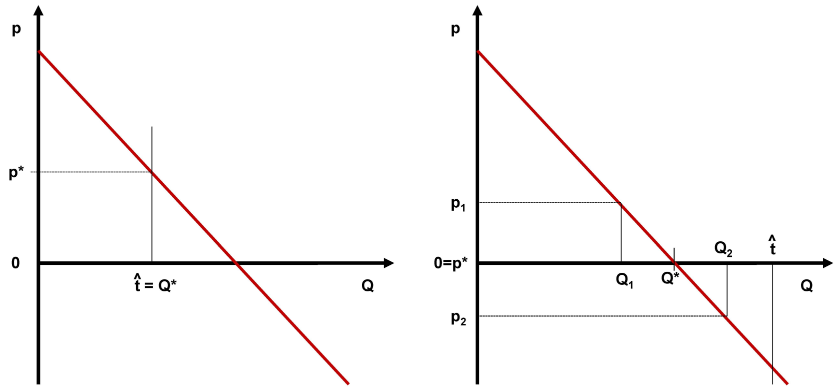


FIGURE 3.1: Basic economics of interconnectors

maximized at a price spread P^* and leads to $Q^* = \hat{t}$. However, provided the available cross-border capacity $\hat{t}$ is more than sufficient to equalize prices (pictured right), the price spread P equals zero and $Q^* < \hat{t}$.

If *implicit* market coupling or market splitting is in place and no further restrictions exist, the chosen quantity Q of cross border transmission flows is equal to Q^* for any given hour. The auction office knows the hourly aggregated supply and demand curves in both market areas and maximizes total welfare accordingly.

In the case of explicit auctioning, market participants who have acquired transmission rights determine the quantity Q. Empirical data shows that market participants do not choose the optimal quantity Q^*, especially when $Q^* < \hat{t}$ (Figure 3.1, right). As previously mentioned, there is a lot of noise in the empirical data due to the incomplete information about the demand for power transmission. However, when the assumption that firms play a Cournot game is valid, then firms must be undershooting on average, meaning that the outcome is *ex-ante* inefficient.

Even though we do not systematically analyze empirical data, we present some heuristic calculations. We apply the following procedure to test for undershooting: After having collected hourly power exchange prices and the corresponding supply and demand curves, available cross-border capacities and the actually scheduled flows, we are able to determine the *ex-post* optimal flows Q^*. A solid data base is provided for the German-French interconnector from the 1st of January 2009 to 8th of November 2010 and for the German-Swiss interconnector from the 1st of March 2011 to the 31st of December 2012.[82] Filtering for hours in which the scheduled flow was from Germany to France but the available capacity was not fully utilized, we narrow down the analysis to 6073

[82]Hourly power exchange prices and supply and the corresponding supply and demand curves for the market areas France, Germany and Switzerland were provided by the *European Power Exchange* (EPEX, 2013), available cross-border capacities and scheduled flows by the *European Network of Transmission System Operators for Electricity* (ENTSO-E, 2013b).

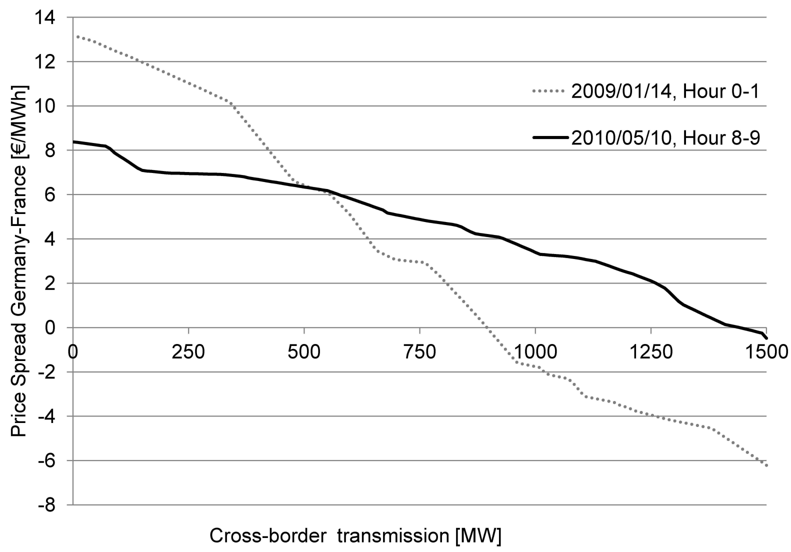


FIGURE 3.2: From the hourly supply and demand curves provided by *EPEX* (former *EEX* and *Powernext*) for the market areas Germany and France, the demand curve for cross-border transmission flows is derived. Two randomly chosen actual demand curves (for the 1st hour of the 14th of January 2009 and the 9th hour of the 10th of March 2010) from Germany to France are shown.

hourly observation points. While the average optimal flow amounted to 1580 MW, the actual flow was only 1453 MW. Hence, average undershooting amounted to 127 MW or 8.0 percent, which is significantly lower than the optimal flow at the 1% level. For illustration, two randomly choosen actual demand curves are shown in figure 3.2. Similar results can be obtained for the German-Swiss interconnector with 2578 observation points. While the average optimal flow amounted to 545 MW, the actual flow was only 516 MW. Hence, average undershooting amounted to 29 MW or 5.4 percent, which is significantly lower than the optimal flow at the 1% level.

3.3.2 Auction Offices and Information Levels

Auction offices were recently subject to constant changes. Today, there are two main organizations in Europe, the *Capacity Allocating Service Company (CASC)* and the *Central Allocation Office (CAO)*.[83] Additionally, there are other platforms like *DAMAS*, *KAPAR* and the French TSO *RTE* that conduct daily cross-border auctions.[84]

[83]CASC is currently operating daily cross-border capacity auctions at the Austrian-Swiss, Austrian-Italian, German-Swiss, French-Swiss, French-Italian, Greek-Italian and Swiss-Italian borders. Website: www.casc.eu. CAO is currently operating daily cross-border capacity auctions at the Austrian-Czech, Austrian-Hungarian, Austrian-Slovenian, Czech-German, Czech-Polish, German-Polish and the Polish-Slovakian borders. Website: www.central-ao.com. Last Update: 20th of September 2012.

[84]Daily cross-border auctions based on the DAMAS system are currently conducted at the French-English, Bulgarian-Romanian, and Hungarian-Romanian borders, among others. Daily cross-border auctions based on the KAPAR system operated by the Hungarian TSO MAVIR are currently conducted at the Hungarian-Croatian and the Hungarian Serbian borders. Last update: 20th of September 2012.

In order to understand the inefficiencies in the second stage of explicit auction regimes, we first have a closer look at the auction offices and the information about the first-stage results passed to the traders. While some offices give detailed information about the number of successful bidders in the first stage (coincides with the number of firms in the second stage), others do not. The same holds true on how capacities are split among the firms. We analyze three explicit auction regime settings:

Complete information: The number of firms and their endowments with capacity are known to all firms,

Incomplete information: Each firm solely knows its own endowment, the number of competing firms is unknown,

Partial information: Each firm knows its own endowments and the number of other firms, but does not no know their rival's endowment.

There is at least one auction office providing *complete information* for day-ahead capacity auction results. Using the DAMAS System, the Romanian TSO *Transelectrica*, for example, currently publishes the number of successful auction participants, their names and their allocated capacities.[85] The *incomplete information* design, in which very little information about the number of successful bidders is published, is currently used by *RTE* at the French-Spanish Border and has been in operation at several other borders in the past. One prominent example was the German-French interconnector used before market-coupling started in November 2010. RTE merely publishes the number of successful bidders per day for daily auctions, meaning that firms know the maximum number of competitors for each hour but do not know how many competitors are endowed with a positive amount of capacity in a given hour. CASC and CAO currently publish *partial information*. They provide the number of successful bidders, but not precisely how capacities are split amongst them.

In the next section we present the general model framework, which is able to capture the information regimes as described above.

3.4 The Model

We consider a set of firms $N = \{1, 2, \ldots, n\}$. Firms may face uncertainty with respect to the other firm's endowment of transmission capacity. In a Bayesian approach, a strategy

[85] Transelectrica is currently conducting explicit day-ahead auctions at the Bulgarian-Romanian and Hungarian-Romanian borders. https://www.markets.transelectrica.ro/public. Last update: 20th of September 2012.

of firm i is a decision rule that specifies a firm's amount of transmitted electricity for every possible information set with which the firm may be endowed. The amount of transmitted electricity corresponds to a firm's output in the Cournot model setting, and we use the terms *transmission* and *output* interchangeably.

We denote $T \subset \{0, 1, 2, \ldots\}$ as the finite set of possible capacity levels and $\Omega = \prod_{n \in N} T$ as the set of possible states of nature. The common prior belief μ is a probability measure on Ω. An element of Ω, which is a capacity allocation among all n firms, is denoted by $\omega = (\omega_1, \omega_2, \ldots, \omega_n)$. We assume that every firm is endowed with a production capacity exceeding zero with positive probability. The information with which a firm is endowed when making its output decision is described by a random variable T_i on Ω.[86] A strategy is a function $q_i(T_i(\cdot))$ satisfying $q_i(T_i(\omega)) \leq \omega_i$. Lastly, we denote S_i as the strategy space of firm i and $S = \prod_{i=1}^{n} S_i$ as the space containing all strategy profiles.

As previously defined, $q_i(T_i(\omega))$ is the output of firm i. We let $Q(\omega) := \sum_{i=1}^{n} q_i(T_i(\omega))$ denote the overall output. The inverse demand function $P(Q)$ corresponds to the price difference between two electricity markets. We assume that P is linear and decreasing with total industry electricity transmission Q. We do not consider costs, since exercising transmission rights is costless.

The *state-dependent payoff function* u_i of firm i is given by

$$u_i(\omega, q_i, q_{-i}) = q_i(T_i(\omega))P(Q(\omega)). \tag{3.1}$$

A strategy profile $q \in S$ is a *Bayesian Cournot equilibrium* if for every i and $\tilde{q}_i \in S_i$ the *expected payoff function* is maximized,

$$E\left[u_i\left(\cdot, q_i, q_{-i}\right)\right] \geq E\left[u_i\left(\cdot, \tilde{q}_i, q_{-i}\right)\right], \tag{3.2}$$

meaning that in an equilibrium no firm has an incentive to unilaterally deviate from its strategy. Maximizing (3.2) is equivalent to maximizing the *conditional payoff expectation*, so that

$$E\left[u_i\left(\cdot, q_i, q_{-i}\right) \mid T_i(\omega)\right] \geq E\left[u_i\left(\cdot, \tilde{q}_i, q_{-i}\right) \mid T_i(\omega)\right] \tag{3.3}$$

for all $i \in N$ and all $\omega \in \Omega$.[87]

Remark 3.1. Linearity of inverse demand ensures that the state-dependent payoff function (3.1) is concave in the output of firm i. Moreover, concavity is inherited by the expected payoff function (3.2) (Einy et al., 2010). Since a firm's strategy space is compact and convex, Nash's theorem implies the existence of an equilibrium.

[86] The information sets of firm i are then the elements of the $\sigma-$algebra $\sigma(T_i)$ generated by T_i.

[87] See Harsanyi (1967-69) and Einy et al. (2002).

As previously mentioned, we analyze three schemes of information. In terms of the model formulation, the case of complete information corresponds to $T_i(\omega) = \omega$ for all $i \in N$ and all $\omega \in \Omega$. Thus, every firm is perfectly informed. When firms only know their own transmission capacity, then $T_i(\omega) = \omega_i$ holds. Finally, when information is partial, meaning that the number of active firms is known, then $T_i(\omega) = (\omega_i, F(\omega))$, where

$$F(\omega) = |\{i \in N : \omega_i > 0\}|.$$

In the next section we construct equilibrium strategies for the case of complete information. Moreover, for the case of three firms we provide a technique to numerically derive equilibrium strategies when information is incomplete.

3.4.1 Complete Information

This question of existence and uniqueness of equilibrium strategies in this setting is treated extensively in the literature.[88] However, we provide a constructive proof on existence and uniqueness, which coincidently is helpful for the simulations. Speaking in terms of the model formulation, we discuss the case of $T_i(\omega) = \omega$ for all i and all ω.

We arbitrarily choose a capacity configuration $\omega = (\omega_1, \omega_2, \ldots, \omega_n)$. Without loss of generality, we assume that $\omega_i \leq \omega_j$ if $i < j$. We let q_i denote the output of firm i and write $q = (q_1, q_2, \ldots, q_n)$. The firm's equilibrium strategy of the corresponding unrestricted Cournot oligopoly is denoted by q^C. We define

$$q_1(\omega_1, \omega_2, \ldots, \omega_n) = \min\left\{\omega_1, q^C\right\}. \tag{3.4}$$

Firm 1 produces the $n-$firm Cournot quantity, whenever possible, and otherwise all of its capacity ω_1. If $q(\omega_1, \omega_2, \ldots, \omega_n) = q^C$, we define

$$q_j(\omega_j, \omega_1, \omega_2, \ldots, \omega_{j-1}, \omega_{j+1}, \ldots, \omega_n) = q^C$$

for all $j \geq 1$. If not so, we consider the $n-1$-firm oligopoly in which firms $i = 2, 3, \ldots, n$ face residual demand resulting when firm 1 produces ω_1. We let q^C_{n-1} denote the Cournot output of the corresponding unrestricted oligopoly and define

$$q_2(\omega_2, \omega_1, \omega_3, \ldots, \omega_n) := \min\left\{\omega_2, q^C_{n-1}\right\}.$$

[88] See for example Bischi et al. (2010).

By iteration, we obtain a strategy for every firm with the following property: There exists a threshold $k \in N$ so that $q_i(\omega_i, \omega_{-i}) = \omega_i$ for all $i < k$ and $q_i(\omega_i, \omega_{-i}) = q_k(\omega_k, \omega_{-k}) < \omega_k$ for all $i \geq k$, following from the construction procedure.

If in equilibrium there is a firm with a binding capacity restriction, the total output of the industry is lower compared to the output of the standard form Cournot oligopoly. This property is derived from the slope of the best response function r, which exceeds -1. If one firm decreases its output due to its capacity restriction, then the corresponding increase of the other firms is smaller. The following proposition sums up the well-known results we reconsidered in this section.

Proposition 3.2. *The strategy constructed above is the unique and symmetric complete information equilibrium of the Cournot oligopoly. If there exists an* $i \in N$ *such that* $\mu\left(T_i < q^C\right) > 0$*, then the expected total output in the complete information equilibrium is smaller compared to the total output of the unrestricted Cournot oligopoly.*

All proofs are provided in the Appendix of this thesis on page 101.

3.4.2 Incomplete and Partial Information

The results provided in this section cover both the case of incomplete information and the case of partial information defined on page 61. Since we seek to solve the model numerically, we provide an algorithm converging to a unique equilibrium solution, which then must be symmetric.

While equilibrium strategies can be explicitly constructed in the case of complete information, as demonstrated in the last section, this task is challenging when information is incomplete. In the very general model setting presented on page 61, equilibrium strategies can be of any shape since the common prior belief is left unspecified.[89]

However, in the context of exercising cross-border capacity, we can impose two restrictions on the common prior belief. First, firms are *ex-ante* symmetric by assumption. This leads to the following requirement:

$$\mu\left(T_i = t\right) = \mu\left(T_j = t\right) \text{ for all } t \in T \text{ and } i \neq j. \tag{3.5}$$

Second, we explicitly allow for firms to be endowed with zero capacity with positive probability. In particular, given that firm 1 is endowed with some capacity level t, then,

[89]See Richter (2013) for an example.

with positive probability, firm 2 is endowed with zero capacity as long as there are at least three firms participating. This leads to

$$\text{If } n > 2, \text{ then } \mu\left(T_2 = 0 | T_1 = t\right) > 0 \text{ for all } t \in T. \tag{3.6}$$

Conditions (3.5) and (3.6) do not sufficiently specify the common prior belief to allow for an analysis of the shape of equilibrium strategies. To provide intuition for that, we consider the following construction procedure for the common prior belief. Let $\tilde{\mu}$ be an arbitrarily chosen probability measure on the product space $\prod_{i=1}^{n} T$ such that $\tilde{\mu}$ meets conditions (3.5) and (3.6). If T_i denotes the capacity with which firm i is endowed and if $\hat{t}$ denotes the overall cross-border capacity, we can define

$$\mu(\,\cdot\,) := \tilde{\mu}(\,\cdot\,|\sum_{i=1}^{n} T_i = \hat{t}).$$

Thus, we can choose almost any distribution for $\tilde{\mu}$ and obtain the corresponding common prior belief μ. Even for a simple $\tilde{\mu}$, the conditional distribution μ is difficult to handle.

However, conditions (3.5) and (3.6) enable us to prove the existence of a unique Bayesian-Cournot equilibrium for the case of three firms. We show that under conditions (3.5) and (3.6), the industry's best response function $\tilde{r}$ is a contraction mapping, meaning that if we iterate the best response function, then the sequence we obtain converges to the unique equilibrium solution.[90]

Therefore, we derive the best response function of the model. For a given strategy profile $q = (q_1, q_2, \ldots, q_n)$, we write $q_{-i} = \sum_{j \neq i} q_i$ and define for $t \in T$ and $i \in N$

$$\tilde{r}_i(t, q_{-i}) = \min\left\{t, r\left(E\left[(q_{-i}|T_i = t]\right)\right\}.$$

Thus, $\tilde{r}_i(t, q)$ is the best response function of firm i when it is endowed with capacity t, given that the other firms apply q_{-i}. This stems from linear demand, since then the best reply function r of the unrestricted Cournot oligopoly only depends on the expected output of the other firms $j \neq i$. We define

$$\tilde{r}(q) := (\tilde{r}_i(t, q_{-i}))_{i \in N, t \in T}$$

to be the vector of best responses in each state and for each firm. Then a fixed point of $\tilde{r}$ is an equilibrium. Theorem 1 states that the iterated best response function converges to

[90] More precisely, there exists $\theta < 1$ and a metric d on the space S of strategy profiles so that

$$d(\tilde{r}(q), \tilde{r}(q')) \leq \theta d(q, q')$$

for all strategy profiles q, q'. Moreover, S needs to be complete with respect to d. Then, the sequence $x_n := \tilde{r}(x_{n-1})$ converges to some element x that does not depend on x_0. Completeness with respect to d ensures that x is an element of S.

the unique fixed point. While we cannot derive equilibrium strategies analytically, Theorem 1 implies that we can numerically implement the iterated best response algorithm for any common prior belief and obtain the unique equilibrium solution.

Theorem 1. Under conditions (3.5) and (3.6) and when $n \leq 3$, for any q_0 the sequence

$$q(n) := \tilde{r}(q(n-1))$$

converges to the unique fixed point q that does not depend on the choice of q_0. In particular, a unique equilibrium exists, which then must be symmetric.

3.5 Numerical Solution to the Model

We solve the model numerically and compare the corresponding market outcomes by means of social welfare, producer surplus and consumer surplus for the three information regimes *incomplete information (II), partial information (PI)* and *complete information (CI)*. For the simulation, we assume that inverse demand is given by $p(q) = 6 - q$. We allow for 21 capacity levels, starting at 0 and ending at 5. The distance between any two capacity levels is constant and equal to 0.25. Lastly, we assume that μ is uniformly distributed on the set of feasible capacity levels.

3.5.1 Equilibrium Strategies

In Figure 3.3 A, the equilibrium strategy for the incomplete information setting is pictured. On the horizontal axis, the capacity with which a firm is endowed is plotted and on the vertical axis, we can see the corresponding output. The symmetric equilibrium strategy is strictly increasing with a firm's capacity. As in the i.i.d.-case analyzed by Richter (2013), firms fully utilize their capacity up to a threshold. Then, a bend occurs and the strategy is increasing up to the monopoly output in a convex manner. Indeed, a firm must produce its monopoly output when it is endowed with maximum capacity, since then the firm is facing a monopoly with complete information.

Next, we consider Picture B, in which the PI-equilibrium strategy q^{PI} is plotted (to some extent). Because q^{PI} is a function of two arguments (capacity of a firm and number of active players), we cannot directly plot it in Figure 3.3, and a three-dimensional chart is unfortunately not instructive. Therefore, we define $q^{PI}_{\min}$ to be

$$q^{PI}_{\min}(\omega_i) = \min\{q^{PI}(T_i(\tilde{\omega}))|\tilde{\omega}_i = \omega_i\}.$$

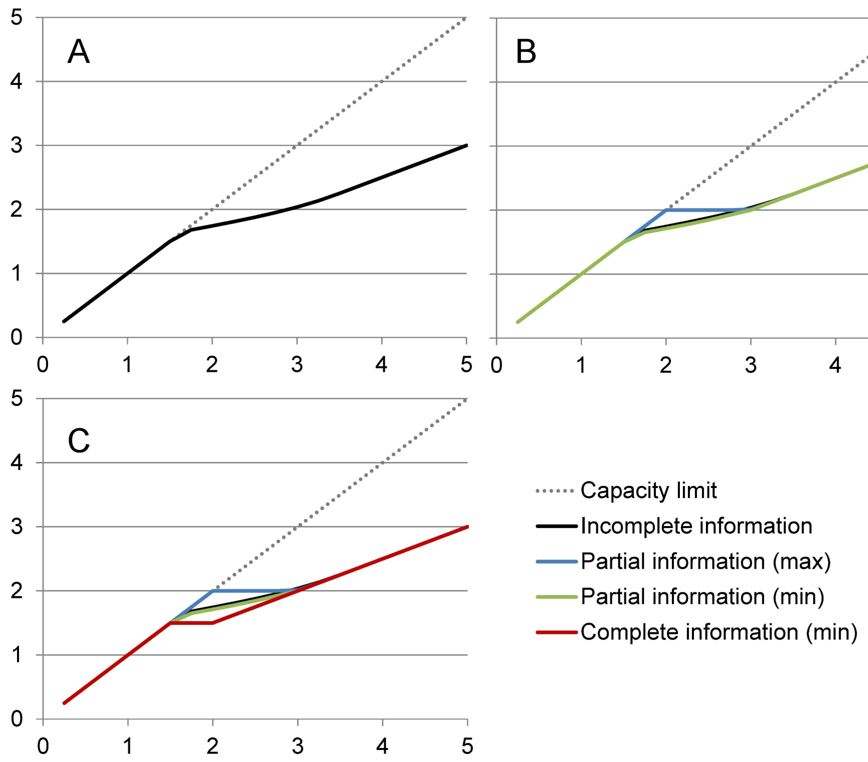


FIGURE 3.3: Numerically derived equilibrium strategies

Thus, for a given capacity level ω_i, we pick the smallest equilibrium output among all possible numbers of active players given ω_i. The number $q^{PI}_{\max}$ is defined accordingly and, as seen in the example, $q^{PI}_{\max}$ equals q^{PI} if and only if there are two or less active firms. In the example, a firm has complete information when knowing that there is only one competitor.

We can see that the PI-strategy exceeds the II-strategy on a certain range (if the number of active firms is low) and the other way around (if the number of active firms is small). The range $[2, 3]$ corresponds to the event $(2, 3, 0)$ (or a permutation) in which two firms produce their two-player Cournot quantity. Moreover, for large capacity values, both strategies converge: If firm 1 is endowed with a sufficiently large amount of capacity, the other firms fully utilize their capacity in both information settings.

Lastly, we depict a similar modified strategy for the case of complete information in Picture C. The corresponding maximal strategy $q^{CI}_{\max}$ coincides with $q^{PI}_{\max}$ because in both cases, firms face complete information. The corresponding minimum strategy $q^{CI}_{\min}$ is smaller than the other strategies, since under complete information, a firm can protect itself against the case in which all three firms have roughly the same amount of capacity. In fact, in the range $[1.5, 2]$, the strategy $q^{CI}_{\min}$ corresponds to the case in which every firm produces its Cournot quantity, which corresponds to the event $(2, 1.5, 1.5)$ (or a permutation).

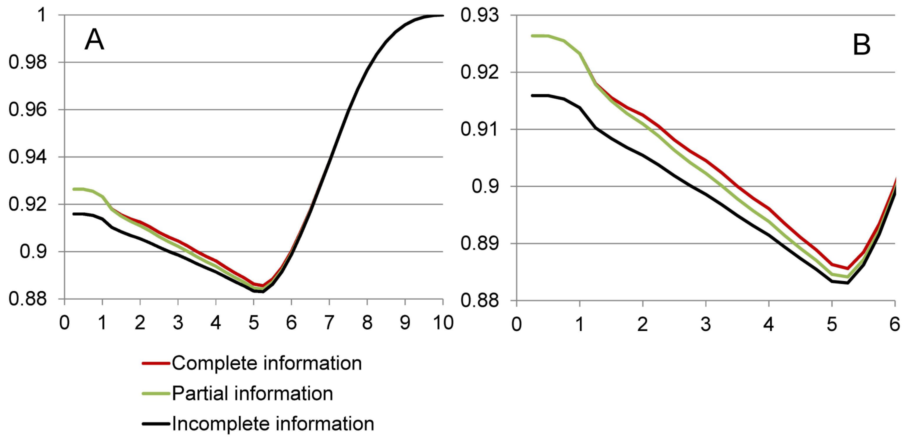


FIGURE 3.4: Effects of information sharing on social welfare

3.5.2 Social Welfare

In this section, we analyze expected social welfare for the different information regimes and different demand intercepts. We express the expected welfare achieved under a given scheme of information and for a given demand intercept as a share of the maximal achievable welfare. When the demand intercept exceeds total capacity, welfare is maximized if and only if every firm utilizes all of its capacity. When the demand intercept is smaller than total capacity, welfare is maximized at the demand intercept.

As previously defined, the random variable $Q(\omega)$ denotes the industry's realized output. Consumer surplus is equal to $CS(\omega) := Q(\omega)^2/2$ and producer surplus is given by the aggregate industry profit $PS(\omega) := Q(\omega)P(Q(\omega))$. We define realized social welfare to be $CS(\omega) + PS(\omega)$.

Figure 3.4 shows the expected welfare for the different schemes of information. On the horizontal axis, the demand intercept is plotted. On the vertical axis, we can see the expected share of maximum achievable welfare (Figure 3.4 B is an enlargement of Figure 3.4 A).

The expected welfare in the complete information regime and the partial information scheme coincide when the demand intercept is sufficiently small. In this setting, firms do not fully utilize their capacities (as long as capacity is exceeding zero). Therefore, firms have complete information when they are informed about the number of active firms.

Furthermore, relative expected welfare approaches unity as the demand intercept approaches 10 in all information regimes. Apparently, this is because then every firm fully utilizes its capacity in every information regime and in every state of nature. In this case, we have defined the maximum achievable welfare to be full utilization of total capacity. Via similar reasoning, the curve is increasing on the right-hand side of its local minimum. Therefore, relative expected social welfare is high when either capacity limits are rarely active (when the demand intercept is small, case 1) or when they are rarely redundant (when the demand intercept is high, case 2).

Equivalently speaking, expected social welfare is low if, with high probability, a firm with a large capacity can act as a monopolist on residual demand, since the other firms have little capacity and thus fully utilize it. In this case, the dominant firm leaves a large share of capacity unused. This follows from the slope of the best response function, which is equal to $-1/2$.

The impact of the slope of the best response function on total electricity transmission becomes smaller in case 1 and vanishes in case 2 as defined above. In case 1, in which the demand intercept is relatively small compared to total cross-border transmission capacity, firms do not fully utilize their capacity, since their capacity limits exceed the Cournot quantity of the unrestricted game. Therefore, if the demand intercept is sufficiently small, partial information is equivalent to complete information, whereas firms face uncertainty with respect to the number of active firms in the case of incomplete information.

In case 2, in which the demand intercept is relatively large compared to total cross-border transmission capacity, every firm fully utilizes its capacity, regardless of the observed capacity allocation. In this case, the equilibria of all three information regimes coincide.

Lastly, Figure 3.4 shows that social welfare increases with the level of information. This is the is the main result of the paper. Figure 3.5 compares expected welfare for different settings for the case in which the demand intercept equals 3. In the competitive market outcome, total output equals the demand intercept. Consumer surplus and social welfare coincide, since marginal costs are zero, and are equal to $3^2/2 = 4.5$. The outcome of the unrestricted Cournot oligopoly leads to an output of $9/4$. This leads to a dead weight loss of $(3-9/4)^2/2 = 9/32$, thus implying that social welfare is equal to $4.5-9/32 \approx 4.22$. To sum up, we can identify three driving forces reducing welfare.

First, Cournot behavior of firms reduces welfare, a well-known fact that holds in any Cournot oligopoly setting.

Second, capacity constraints reduce welfare, even when total capacity exceeds the demand intercept and firms have complete information. This result is already indicated by Proposition 1, which states that in the presence of capacity constraints, the expected total transmission of electricity declines. The effect on welfare is initially unclear; however, Figure 3.5 shows that due to capacity constraints, welfare decreases.

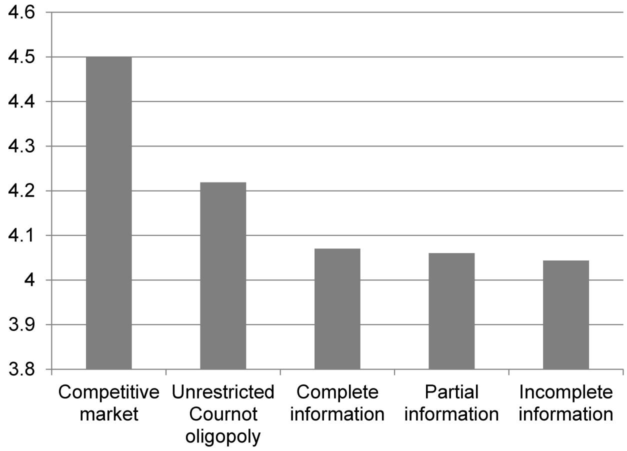


FIGURE 3.5: Expected welfare in different information regimes

Third, a reduction in information reduces welfare. The information effect is systematic but small; however, if we chose a common prior belief with a higher variance, the effect would probably become stronger.[91] The next two sections seek to explain the information effect on social welfare. The main driving force is the variance of total electricity transmission.

3.5.3 Consumer and Producer Surplus

We demonstrate that the increase of social welfare induced by information sharing is driven by an increase in producer surplus, whereas the effects on consumer surplus are small and partly ambiguous. When firms are better informed, they coordinate better on total industry output. This lowers the variance of total output, which decreases consumer surplus. This effect on consumer surplus is clearly observable when comparing the incomplete information equilibrium with the complete information equilibrium. However, the effect is less clear when we compare the partial information equilibrium with the complete information equilibrium.

3.5.3.1 Producer Surplus

As before, we calculate a relative number: We define the maximum achievable producer surplus to be the minimum of the maximal capacity and the aggregate industry output of the standard form Cournot oligopoly. Then, we consider the ratio of expected producer surplus and maximum achievable producer surplus.

Figure 3.6 shows that the effect on producer surplus is similar to the effect on social welfare – producer surplus increases with the level information. However, there are states

[91] Richter (2013) discusses the impact of the variance of the common prior believe on results of information sharing in a similar context.

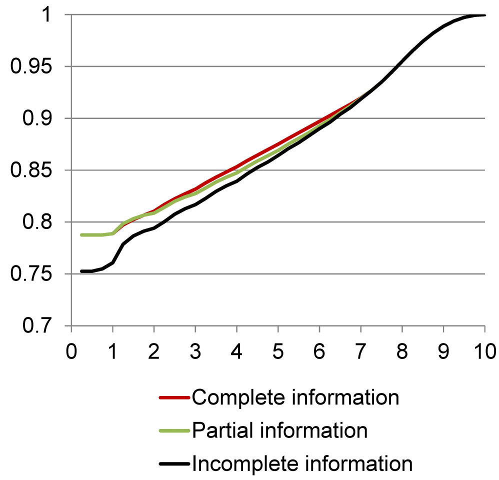


FIGURE 3.6: Effects of information sharing on producer surplus

of nature in which producer surplus can decrease due to information sharing: When there are two firms A and B that do not fully utilize their capacity in the incomplete information equilibrium, and when some firm C is endowed with zero capacity, then revealing this information induces firms A and B to increase their output. This is because the incomplete information output of firms A and B takes into account the possibility that there are three active firms rather than two. To give an example based on the simulation results, we consider the case in which the demand intercept is equal to 1. Firm A has a capacity that is equal to 2 and firm B has a capacity that is equal to 5. Under incomplete information, firm A produces 0.253, whereas firm B produces 0.296. That is to say, A and B take into account that the remaining capacity is (evenly) split up between two firms, which is why A and B produce less than the Cournot quantity, which is equal to 0.333. These equilibrium outputs lead *ex-post* to payoffs that are equal to 0.114 and 0.133, respectively. The complete information output of A and B equals 0.333, leading to a payoff that is equal to 0.112.

Similarly, there are states of nature in which producer surplus increases when information is shared. The simulation results show that this is always true as long as there are one dominant firm and two firms with little or zero capacity. Then, the small firms overestimate total industry output under incomplete information, and, as a consequence, their outputs are *ex-post* too low. Therefore, when information is shared, small firms increase their output. Because total industry output is relatively low due to the presence of a large firm, the marginal revenue of an increase of output is positive. Thus, the small firms gain from sharing.

Notice that in every information regime the outputs of the firms are negatively correlated. This is because if a firm is endowed with a large share of cross-border capacity, the other

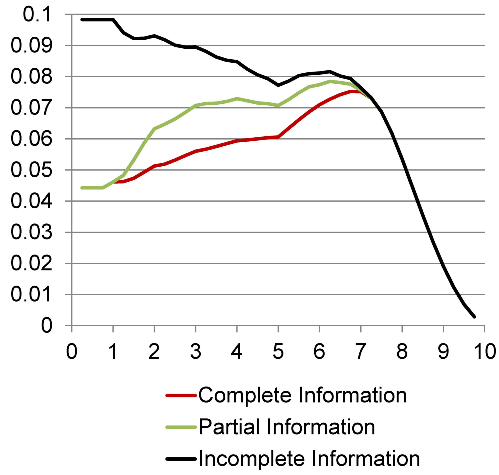


FIGURE 3.7: Effects of information sharing on the standard deviation of total industry output

firms are endowed with little capacity. As a consequence, the variance of total output decreases.

Apparently, the absolute value of the correlation of outputs increases with the level of information, regardless of the choice of the common prior belief. This is because firms transmit some "average" amount of electricity when they have little information. Figure 3.7 shows that the variance of total output is decreasing with the level of information. Since consumer surplus is increasing with the variance of total industry output (see Richter (2013) or Shapiro (1986)), Figure 3.7 indicates that consumer surplus decreases with the information with which firms are endowed.

3.5.3.2 Consumer Surplus

Figure 3.8 A shows that consumer surplus varies with the demand intercept in a similar fashion as social welfare. Starting at 0.53, a local minimum of 0.45 is attained when the demand intercept equals 5. Apparently, the effect of different information regimes on consumer surplus is small.

Figure 3.8 B enlarges the range $[0, 5]$. The expected consumer surplus in the incomplete information setting weakly exceeds both the complete information and partial information consumer surplus. However, in the case of partial information, consumer surplus can be above and below consumer surplus resulting from complete information. Thus, a clear statement regarding the impact of information sharing on consumer surplus can not be obtained.[92] However, Figure 3.7 shows that we can identify one stable result with respect to consumer surplus: The standard deviation of total output is decreasing with

[92]This is a common issue, seen for example in Raith (1996).

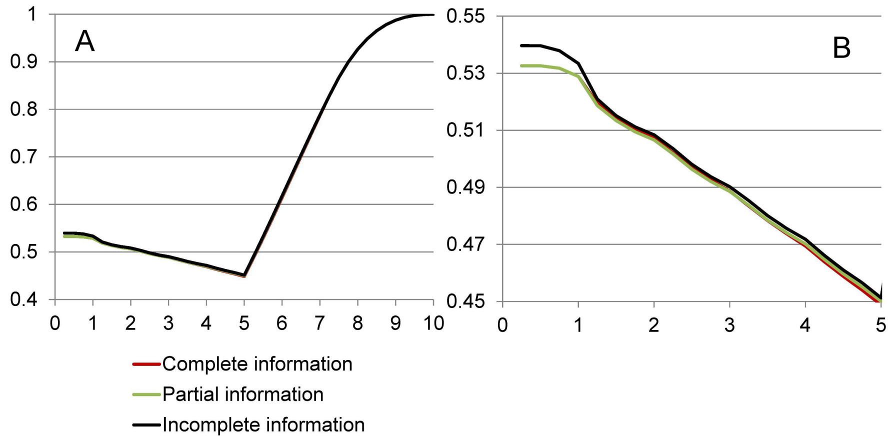


FIGURE 3.8: Effects of information sharing on consumer surplus

the level of information, which in turn decreases consumer surplus. To sum up, the impact on consumer surplus is small, and increasing information tends to reduce consumer surplus. The same holds true for expected electricity transmission. This follows from the fact that the variance of total output is decreasing and from the fact that consumer surplus is increasing with both variance of total output and expected total output.

3.6 Results and Discussion

We analyzed the strategic behavior of firms endowed with transmission rights that arises when transmission capacity between electricity markets is explicitly auctioned. In doing so, we perceived the strategic behavior of firms as a Cournot oligopoly in which firms face incomplete information with respect to the other firms' transmission rights.

Thereby, total cross-border capacity is common knowledge, which enables a firm to calculate the conditional distribution of the other firms' transmission rights given its own amount of transmission rights (the case of *incomplete information*). Moreover, we allow for an information regime in which the number of firms endowed with a positive amount of transmission rights is also revealed to the firms (the case of *partial information*).

For the case of three or less firms, we have shown that the best response function is a contraction, a result that is specific to the special setting under consideration. The best response function converges to the unique Bayesian Nash equilibrium, which, in particular, must then be symmetric. Because the best response function converges, we were able to calculate equilibrium solutions by means of simulation and to perform a sensitivity analysis with respect to the demand intercept. Moreover, we calculated the equilibrium for the case of complete information.

By comparing the equilibria for the three information regimes, we find that revealing information to firms increases social welfare. The increase of social welfare is driven by an increase in producer surplus. The states of nature that potentially diminish producer surplus are overcompensated by states of nature in which producer surplus increases. Since information sharing increases the negative correlation of the firms' outputs, the variance of total industry output decreases.

Although a decrease of the variance of total industry output in general decreases consumer surplus, the effect on consumer surplus is smaller than on producer surplus. We find that expected consumer surplus decreases when moving from the incomplete information equilibrium to the partial information or to the complete information equilibrium. However, when moving from the partial information equilibrium to the complete information equilibrium, the effect on consumer surplus is ambiguous. As a consequence, the same holds for total electricity transmission.

Thus, we identified three forces regarding capacity auctions that diminish social welfare: First, firms play a Cournot game, which prevents an efficient market outcome. Second, the presence of capacity constraints further reduces social welfare. This is derived from the slope of a firm's best response function, which exceeds -1: When a firm with little capacity fully exercises its transmission rights, its lack of transmission is not fully compensated by those firms endowed with a large amount of transmission rights. Third, incomplete information reduces welfare as well, as in the presence of incomplete information, firms exercise their transmission rights less aggressively.

As mentioned in the introduction, explicit capacity auctions are in fact a two-stage game. In the first stage, the transmission rights are auctioned. Then, firms are informed about their own amount of transmission rights (and, depending on the auction office, the number of active firms). In the second stage, firms exercise their transmission rights. The model analyzed in the paper at hand could be expanded to a two-stage game such as the following example.

Before the first step of the auction process is conducted, firms observe signals about a common value, for example the demand intercept of the inverse demand function. The action space of the first stage can be modeled via linear bidding functions that are decreasing, mapping transmission capacity to a price. The horizontal intercept of each firm's bidding function could be modeled as an increasing function of the firm's signal. The market operator then selects the highest bids and assigns transmission rights to the firms. When firms make their output decisions in the second step, the transmission rights of the other firms are stochastic – the corresponding distribution is induced by the distribution of the signals observed by the firms before the first step of the auction was conducted. Thus, the second stage game is equivalent to the game analyzed in the paper at hand. The results on the three driving forces diminishing social welfare should be stable even when the problem is modeled as a two-stage game.

As previously mentioned, implicit auction regimes clearly outperform explicit auction regimes. Nevertheless, as long as explicit auction regimes are still in place, we recommend that auction offices provide as much information as possible about the first stage results in order to maximize social welfare.

Multi-unit multiple bid auctions in balancing markets: an agent-based Q-learning approach

This chapter is joined work with my co-authors Stefan Lorenczik and Raimund Malischek.

Abstract

There is an ongoing debate on the appropriate auction design for competitive electricity balancing markets. Uniform (UPA) and discriminatory price auctions (DPA), the prevalent designs in use today, are assumed to have different properties with regard to prices and efficiencies. These properties cannot be thoroughly described using analytical methods due to the complex strategy space in repeated multi-unit multiple bid auctions. Therefore, using an agent-based Q-learning model, we simulate the strategic bidding behaviour in these auctions under a variety of market conditions. We find that UPAs lead to higher prices in all analysed market settings. This is mainly due to the fact that players engage in bid shading more aggressively. Moreover, small players in UPAs learn to free ride on the price setting of large players and earn higher profits per unit of capacity owned, while they are disadvantaged in DPAs. UPAs also generally feature higher efficiencies, but there are exceptions to this observation. If demand is varying and players are provided with additional information about scarcity in the market, market prices increase only in case asymmetric players are present.

4.1 Introduction and motivation

The relative performance of different auction designs both in terms of efficiency and prices has been a controversial issue for many years. This is particularly true when it comes to more complex settings such as repeated Multi-Unit Multiple Bid (MUMB) auctions. In multi-unit auctions the auctioneer buys several units of the same good and bidders are allowed to place several bids.[93] In contrast to single-bid auctions, classical closed-form solutions are not available for multiple bid auctions as bidders might engage in bid shading, i.e., they might increase bid prices in order to maximise expected profits. Another layer of complexity is added if auctions are hold repeatedly, information about auction results vary, secondary markets exist or players are asymmetric, either in terms of their size or costs. The most common auction designs are Uniform Price Auctions (UPAs) in which every successful bid receives the marginal clearing price and Discriminatory Price Auctions (DPAs)[94] in which every successful bid is paid its bidding price. Vickrey auctions (see Vickrey, 1961) on the other hand are less common.

The above mentioned controversy about performance of alternative auction designs is mirrored in the development of the electricity industry ever since deregulation started and markets began to evolve. Nowadays, most Day-Ahead (DA) electricity markets in Europe are operated by means of transparent, repeated UPAs. However, the picture looks more diverse when it comes to procurement of balancing capacity which is also referred to as Ancillary Services (AS).[95] The European Network of Transmission System Operators for Electricity (ENTSO-E) provides a comprehensive survey on how AS are currently procured and how balancing markets are designed across European countries (ENTSO-E, 2017). The procurement schemes range from several mandatory designs to bilateral arrangements between *Transmission System Operators (TSOs)* and market players to organized markets and hybrid schemes. The United Kingdom and most central European countries such as Belgium, Germany, Austria, Switzerland, the Czech Republic or Slovakia currently apply repeated DPAs to procure most of their balancing capacities (ENTSO-E, 2017). Portugal, Spain, Norway, Greece and Romania on the other hand are preferably using UPAs. Some countries such as France and the Netherlands use

[93] This process is also referred to as competitive bidding, in which bidders compete for the right to sell. Even though not covered in our analysis, our results are valid also for the typical auction case in which bidders compete for the right to buy.

[94] Also referred to as Pay-as-Bid Auctions (PABAs).

[95] In the draft network code on electricity balancing, ENTSO-E (2013a) defines balancing as *"all actions and processes, on all time-scales, through which Transmission System Operators ensure, in a continuous way, to maintain the system frequency within a predefined stability range [...]"*. Any deviations from the planned schedule are defined as *imbalances* and will be balanced by the TSO. In order to do so, the TSO procures beforehand *balancing reserves*, also referred to as *balancing capacity*, from market players (*Balancing Service Providers (BSPs)*). In case of real-time imbalances, the TSO will then call BSPs for the activation of *balancing energy*.

both auction types for different types of balancing capacities. However, even if the same auction type is applied, significant differences exist with regard to the detailed auction rules and the publication of auction results, not only among different countries but also within countries for different types of balancing capacity.

Our motivation is threefold. First, we aim to contribute to the current discussion on European harmonisation of procurement rules by showing how different levels of market concentration affect prices in UPAs and DPAs. This is particularly interesting as policy makers in Europe seem to be undecided which scheme to prefer and as the costs of procurement of balancing capacities are eventually paid by the consumers of electricity. In an earlier version of the Network Code on Electricity Balancing (NCEB), ENTSO-E (2014) stated that the procurement of balancing energy shall be based on marginal pricing (UPAs). However, according to the latest version of the guideline (ENTSO-E, 2017b), each TSO is free to define its rules for procurement of balancing capacity. On the other hand, ENTSO-E (2017a) published a consultation report on the "FCR Cooperation"[96] in which the partner TSOs propose a change from the current DPA to a UPA settlement scheme in the future.

Second, we investigate how the auction types perform in term of efficiency. In the context of our auction game, total welfare is at its maximum if costs are minimized. Hence, we define the 100% efficiency benchmark as an auction result in which only those bids that are associated to the lowest cost capacities have been accepted. While regulators and TSOs in Europe focus mainly on consumer surplus which is equivalent to lower consumer prices in markets with a non-elastic demand, social welfare doesn't seem to be the main objective. However, we believe that the efficiency of the competing auction schemes is an essential feature that should be analysed thoroughly as well.

The third part of our motivation stems from a decision taken by the Bundesnetzagentur for Electricity, Gas, Telecommunications, Post and Railway (BNetzA) in April 2011. With this decision, several auctioning rules for the procurement of balancing capacity, precisely, of Secondary Reserve (SR)[97], were modified (BNetzA, 2011). Of particular interest was the decision to reduce information given to Balancing Service Providers (BSPs) about auction results. Whilst, prior to the decision, accepted (infra-marginal) and non-accepted (extra-marginal) bids have been published, the BNetzA decided that TSOs would only publish accepted bids in the future (Figure 4.1). Even though the agency admitted that this step would reduce transparency in the market, it stated that

[96] The FCR cooperation is a cooperation between several European TSOs including the Austrian TSO APG, the Belgian TSO ELIA, the Danish TSO EnergieNet, the Dutch TSO Tennet, the French TSO RTE, the German TSOs 50Hertz, Amprion, Tennet and TransnetBW as well as the Swiss TSO SwissGrid. Currently, these TSOs hold a common weekly FCR (Frequency Containment Reserve, also referred to as Primary Reserve (PR)-auction.

[97] Also referred to as automatic Frequency Restoration Reserve (aFRR).

the expected benefits were likely to outweigh the negative effects. Especially, the risk of strategic behaviour by pivotal players ought to be reduced. As the market was dominated by a limited number of big players (see Heim and Götz, 2013), the agency believed that the knowledge of prices and volumes of extra-marginal bids might have led to an increase of bid prices by pivotal players (BNetzA, 2011). To the present day, extra-marginal bids are published for Minute Reserve (MR) auctions, but not for SR and PR auctions in Germany.

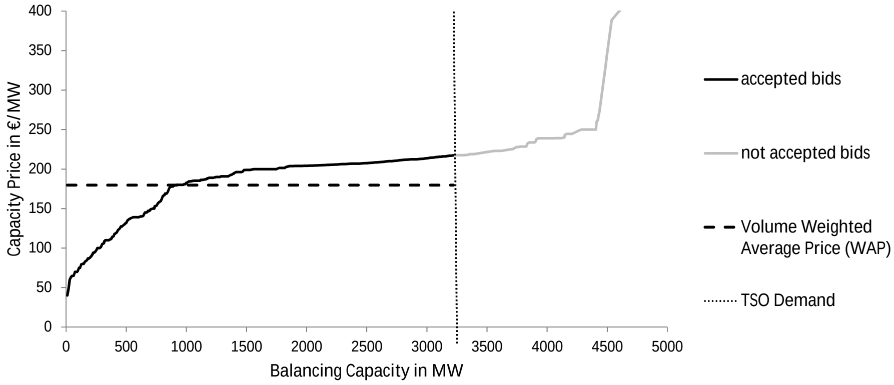


Figure 4.1: Schematic illustration of balancing capacity bids

In the paper at hand we develop an agent-based Q-learning model that allows for comparing UPAs and DPAs in repeated MUMB auctions. The model enables us to investigate a wide range of market settings such as a varying number of players, or player characteristics, such as symmetric or asymmetric players both in terms of size or cost. In a dynamic setting, we vary the demand and control the amount of information that is available to market players about past auction results. Thus, we can test whether information about the supply-demand ratio increases strategic behaviour and consumer prices. Vickrey auctions are not considered in our analysis as they are not found in electricity markets to our knowledge.

First, our results indicate that marginal prices of UPAs turn out to be higher than average prices of DPAs, a result which is valid for all settings. Second, and not surprisingly, we find that with a decreasing number of players and increasing asymmetry between players in terms of size and increasing demand to supply ratios, prices are increasing. With regard to efficiency we observe that UPAs are generally more efficient, but there are some exceptions to this observation. Our analysis with respect to different information regimes shows that prices tend to increase with additional information about the supply/demand ratio only if the number of players is limited and a large asymmetry in terms of size exists.

The remainder of this paper is structured as follows. Section 4.2 provides an overview of related literature, section 4.3 introduces the applied agent-based model and the learning algorithm. Section 4.4 presents the results of our analysis and section 4.5 concludes.

4.2 Literature

4.2.1 Discriminatory (DPAs) vs. uniform pricing auctions (UPAs)

There is a vast amount of literature comparing uniform and discriminatory price auctions. While most analytical papers favour discriminatory pricing in terms of lower consumer prices, experimental and empirical publications find a high degree of collusion in repeated DPAs resulting in possibly higher consumer prices and lower overall efficiency. Fabra et al. (2006) analytically look into how bidding behaviour is affected by the auction format. They start their analysis with a model of two suppliers owning one unit of capacity each of which has to be submitted to the market by one single offer for the entire capacity. Player's capacities and costs are known but asymmetric and demand is certain and inelastic. They find that for high demand, DPA consumer prices are lower in comparison to UPA, while the effect on welfare is ambiguous and subject to the model parameters.[98] Expanding their model to a symmetric oligopoly, Fabra et al. (2006) show by a numerical example that for a given number of suppliers in the DPA, roughly twice as many suppliers are required for the UPA in order to reduce consumer prices to the same level. Frederico and Rahman (2003) analytically compare UPA and DPA with uncertain and elastic demand and perfect information about the cost structure of the industry. In case of perfect competition, they find that a switch from UPA to DPA leads to lower consumer prices, but also to a reduction in welfare. In case of perfect collusion (monopoly), consumer prices and output are lower as well but the effect on welfare is ambiguous. Additionally, they conclude that abuse of market power by the monopolist is harder under DPA. However, if demand is certain, UPA and DPA yield identical outcomes.

On the contrary to most analytical papers, Kahn et al. (2001) strongly argue against a switch from UPA to DPA. They believe that firms will change their bidding behaviour immediately after the introduction of DPA, trying to bid at or slightly below the marginal price. As a result, average DPA prices are equal to UPA prices. However, firms face higher costs in order to forecast the marginal price and overall efficiency is likely to decrease as some low-marginal cost bids might be rejected *"because their bidders have overestimated the market-clearing price"* (Kahn et al., 2001). In the case of imperfect or

[98]For low-demand, prices are competitive and dispatch is efficient for both DPA and UPA.

oligopolistic markets, Kahn et al. (2001) argue that smaller bidders are disadvantaged in DPAs as they have higher forecasting costs per unit of production and are likely to benefit less from exertion of market power by bigger players. Hence, market entry of new players and long-term disappearance of market power becomes less likely. Finally, Kahn et al. (2001) criticise the lower transparency in DPAs which makes it difficult to detect collusive behaviour.

To our knowledge, a publication by Rassenti et al. (2003) is the most detailed experimental study comparing UPA and DPA in complex electricity market environments. Strikingly, they find that *"DPA in a no market power environment is as anti-competitive as a UPA with structural induced market power"*. Rassenti et al. (2003) argue that in an environment with cyclic and revealed inelastic demand, also present in PABAs in German balancing markets, *"the DPA invites sellers to tacitly collude, coordinating their offers without explicit communication at the highest previously observed price in a similar period"*. Similar results were obtained in an empirical study by Heim and Götz (2013) who find collusive behaviour in the DPA for SR in Germany. Using data provided by BNetzA, Heim and Götz (2013) first show that a high degree of market concentration and pivotal players exist. They believe that observed price increases can be traced back to *"repeated pretended bad guessing"* of the clearing price. As a result, firms can profit from increased price levels in later periods of the repeated DPA. Finally, they stress that regulatory authorities are unable to take legal action against abusive behaviour in DPAs as firms can hide behind the *"guess the clearing price principle"* (Heim and Götz, 2013).

4.2.2 Information regimes

Next to the market design, the question which information is available to market participants is of great importance when evaluating the performance of different auction designs, especially in case of repeated auctions. However, most publications choose one particular set of information without variation. To our knowledge, there is little literature that sheds light on the effect of different information regimes in repeated MUMB auctions. Müsgens and Ockenfels (2011) present a qualitative assessment on information feedback in repeated DPAs. The article is written in the context of European balancing power markets and gives an overview of different information regimes. While in some markets there was no feedback at all about past auction results, others publish only the marginal clearing price, the volume weighted average price of all accepted bids or both. The complete bid curve including non-accepted extra-marginal bids (see Figure 4.1) is published only for very few markets. Müsgens and Ockenfels (2011) argue that the publication of the marginal bid price is important for the efficiency of the market. However, they reject that the benefit of additionally publishing extra-marginal bids outweighs the risk of pivotal players increasing their bid prices.

Even though Bower and Bunn (2001) do not vary the information available to players, they explicitly set up a case in which no information about the market outcome or other players' bids is made public. Merely private information and success of own bids at previous auctions is known to players. In the England and Wales electricity market with asymmetric firms, they find significantly higher prices for DPA when compared to UPA as larger firms with more bids can gather more information about past market outcomes due to their sheer size. With UPAs however, all firms with successful bids have the same information about the marginal clearing price.

4.2.3 Agent-based models

Agent-based models have become increasingly popular in economic studies. The applications range from microeconomic topics like the exploration of the supply function equilibrium in Kimbrough and Murphy (2013) or the Cournot equilibrium in Waltman and Kaymak (2008) to more macro-based analysis as for instance presented in Geanakoplos et al. (2012) on systemic risk in the eye of the housing bubble. Applications to energy markets are diverse, naming just exemplarily Bunn and Oliveira (2007) for an analysis of technology diversification or Naghibi-Sistani et al. (2006) for an analysis of bidding behaviour in market based power systems.[99]

One reason for this increasing popularity is that agent-based models allow to analyse situations and problems in which classical closed-form solutions are not available. Further, they allow to increase models complexity and to take into consideration more realistic modelling assumptions and real life market features that are usually excluded from economic analyses. They are also particularly suited in situations in which there is the opportunity for learning due to repeated action. This is for instance the case in daily electricity market auctions.

Agent-based models have also been used to explore the relative performance of UPAs and DPAs. These auction formats are prevalent in electricity day-ahead and balancing market auctions and serve as motivation for our analysis. In MUMB UPAs and DPAs, closed-form solutions are no longer available and hence a particular interesting field to study via agent-based models. A common mistake in analysing these auctions is to directly transfer results from the corresponding single-unit auction to the multi-unit case. In general, results do not transfer from single-unit to multi-unit auctions as shown

[99]Weidlich and Veit (2008) provide an overview of the vast applications of agent-based modelling in energy markets.

for instance in an overview by Krishna (2002) or the literature cited therein. Therefore, in the absence of closed-form solutions, agent-based models provide a valuable option to analyse these auction types. Previous agent-based analysis of UPAs and DPAs include the works of Hailu and Thoyer (2007), Bower and Bunn (2001), Bakirtzis and Tellidou (2006) as well as Xiong et al. (2004). These analyses have painted an unclear picture of the relative performance of the different auctions. Whereas for instance Bower and Bunn (2001) find evidence that prices are higher in DPAs due to the non-availability of market prices, Hailu and Thoyer (2007) argue that there is no clear ordering of the auction formats and results are dependent on the population and the characteristics of supply relative to demand. All studies have assumed a fixed information regime.

Our analysis adds to the existing stream of literature on three key aspects: First and most importantly, we are to our knowledge the first to extend the Q-learning algorithm to a Multi-Unit Multiple Bid (MUMB) set-up, other than Bakirtzis and Tellidou (2006) and Xiong et al. (2004) who use a multi-unit single bid approach. Second, we incorporate demand uncertainty for each consecutive auction. And third, we analyse the effect of different information regimes, i.e., the information about market outcomes that is provided to the players after each round of play. To our knowledge we are the first to incorporate the different information that can be provided to the players into the learning algorithm and to explore its effect systematically.

4.3 The model

We explore bidding strategies of players under different auction and information regimes using an agent-based model. In the model, players bid price-quantity pairs. In doing so, players take into account their costs for providing the good as well as a player specific capacity constraint, i.e., the amount of the good a player can supply. Players have two separate blocks of a fixed size, for which they can make separate bids. We incorporate different bid configurations for each player, ranging from rather flat supply curves to more hockey stick shaped bids. The maximum bid for a block is restricted by an upper bound. The introduction of a price cap is necessary in order to prevent prices to approach infinity as demand is assumed to be inelastic. The minimum possible bid is the player's marginal cost. The inelastic demand is either deterministic or stochastic, based on the setting.

Each auction is repeated many times to enable learning. Also each set-up is repeated several times to check robustness of results. We use the Q-learning algorithm which is a variant of the reinforcement learning approach. Players get feedback on their actions and improve their behaviour in successive rounds of play allowing them to learn from the past through memory.[100] In general, the Q-learning framework consists of a memory-state space which is given by a set S, elements of which are represented by s. s_t then represents the state a certain player is in at time-point t. Agents choose actions $a \in A$ which lead to a transition from state s_t to s_{t+1}. Actions are chosen by drawing from the probability distribution over the action space given by

$$Prob(a) = \frac{\exp(Q_t(s_t, a)/\beta)}{\sum_{a' \in A} \exp(Q_t(s_t, a')/\beta)} \tag{4.1}$$

This representation is also known as the Boltzman exploration strategy and corresponds to a logit model. $Q_t(s_t, a)$ denotes the Q-value of the agent when he is in state s_t and action a. Intuitively, the Q-value represents how favourable the execution of action a in state s_t is. $\beta > 0$ represents the experimentation parameter: the higher the value of β, the more experimentation is performed as the probability $Prob(a)$ of choosing any action a is closer to being evenly distributed. In our implementation, following the literature (see, e.g., Waltman and Kaymak, 2008), we use a gradually decreasing parameter β of the form

$$\beta(t) = 1000 * 0.99995^t \tag{4.2}$$

The parameter β steers the exploration phase and the subsequent transition to the exploitation phase. Using the Q-learning algorithm – as for many other learning algorithms – it is necessary for players to have a sufficiently long exploration phase in which they randomly choose all actions many times to learn about possible pay-offs. After the transition to the exploitation phase is completed, parameter β ensures that players select those actions with the highest expected pay-offs only.

The Q-values of the players are updated after each round of play according to the following rule:

$$Q_{t+1}(s, a) = \begin{cases} (1-\alpha)Q_t(s, a) + \alpha(\pi_t + \gamma \max_{a' \in A} Q_t(s_{t+1}, a')) & \text{if } s = s_t \text{ and } a = a_t \\ Q_t(s, a) & \text{otherwise.} \end{cases} \tag{4.3}$$

$0 < \alpha \leq 1$ and $0 \leq \gamma < 1$ represent the learning parameter and the discount factor. In our setting they are chosen to be 0.5, similar to other analysis in the literature

[100](see, e.g., Bakirtzis and Tellidou, 2006, Kutschinski et al., 2003, Xiong et al., 2004) for previous applications of Q-learning in economic research.

(see, e.g., Waltman and Kaymak, 2008). A lower value of the learning parameter α implies that more weight is put on the old Q-value in the updating process, which can be interpreted as putting more weight on the player's history as compared to recent experience. The γ parameter represents the time preference of the players, with smaller values of γ indicating more myopic behaviour. π_t represents the players pay-off after round t. As a result of the Q-learning algorithm, each players individually learns the optimal behaviour that maximises its pay-off in the long run.

Applied to our MUMB auction, the state s_t of a player at time t is defined by the auction results of the previous round such as the marginal price, the volume weighted average price of all accepted bids and for our uncertainty case (see section 4.4.4) also the level of total demand. Given the state s_t, each player now selects an action a_t according to equation 4.1 which means, he decides at which prices he is going to place his capacity via two bids of equal size into the market. Next, all bids of all players are collected, the market clears and moves to a new landing state s_{t+1}. Each player can now compute its profits and also the maximum Q-value of the new state. These information are now used to update the corresponding Q-value of the initial state (see equation 4.3). After one auction round is concluded, a new auction round begins, this time with the landing stage s_{t+1} as starting point. The less profitable an action is, the lower the Q-value gets and the less often a player selects the corresponding strategy. In the final exploitation phase, a player will only select the strategy with the highest Q-value.

4.4 Simulation and results

4.4.1 Overview

Unlike in energy only markets, there is only very little fundamental information in balancing markets. German TSOs for example merely publish a list of all players on a firm level, but not of the individual units prequalified to provide balancing capacity. Firms might be able to obtain some information regarding the general availability of generation units which are assumed to be able to provide balancing capacity via mandatory messages about planned and unplanned non-usabilities of generation units. However, even if units are available to produce power on the energy-only market, specific technical reasons that do not need to be published might prevent them from providing balancing capacity. Cost calculations are even more complex. First, players are likely to face opportunity costs for selling production units into competing markets like the energy-only market or other balancing markets. Second, it is unknown how competitors split costs between positive and negative balancing capacity in case a unit is sold for positive and negative reserve at the same time, how they estimate added profits from energy calls, how they can reduce capacity costs using the portfolio effect (see also Müsgens et al., 2012) and how they calculate back-up costs in case of unplanned outages. The Q-learning approach is particularly suitable to simulate strategic behaviour in balancing markets as players have very little fundamental information. Therefore, they mainly use historical auction prices as basis for their bidding. The same is true for our Q-learning approach in which prices (and demand levels) are the only information required to define the initial states s_t of each auction round.[101]

We distinguish between three main model settings. We start with the *Base Case* in section 4.4.2, in which demand is constant and all players have capacity costs of zero[102]. We analyse how the number of players, their symmetry in terms of size and different demand levels affect prices of UPAs and DPAs. In the *Cost Case* (section 4.4.3), we allocate costs to the individual players capacities in order to study how the competing auction designs perform in terms of efficiency. Finally, we present the *Uncertainty and Information Case* in section 4.4.4. In this case, we vary the demand from auction to auction within a model run and also modify the information players receive about total demand. In all model settings, players receive information about the state they are in, which is defined by the previous auctions marginal price and the volume weighted average price of all accepted bids. Additionally, information about the demand level is added in our *Uncertainty and Information Case*. Size and costs of a player are always constant within a model run.

On the more technical details: if two or more players bid capacities at the same price and this price is equal to the marginal price, the principle of pro-rata allocation is applied. The price cap is set to 10, the price floor to zero. All players have costs of zero except in the cost case. Each scenario is calculated with either four and/or eight players and different (average) demand levels. We run each case 50 times as a general rule with 400,000 to 700,000 successive auctions in each run. At the beginning of the subsequent auctions, players choose their actions randomly while learning which ones have the highest pay off (exploration phase). Later on, players base their choice on previous experiences: They have learned successful strategies and start to exploit this knowledge (exploitation phase, see also section 4.3). We run each model configuration 50 times with varying seeds for the random number generator. This way we are able to check for more multiple stable outcomes and the robustness of results. The number of auctions per run depends on the complexity of the model settings. In our basic scenario

[101]It is important to work with a limited number of criteria (such as volume weighted average price, marginal price and level of demand) that define states in Q-learning. Otherwise, the memory-state space grows too large and computing time increases.

[102]Cost of zero were chosen arbitrarily, we could have also selected costs of 1 or 2. In the base case it is merely important that costs are constant and equal for all players.

with symmetric players, merely 400,000 successive auctions per run are required before a stable equilibrium is found. With a higher level of (demand) uncertainty, agents require up to 700,000 runs to commit themselves to a limited set of strategies. For our static *Base Case* and *Cost Case* we denote the equilibrium as stable if the average price of the last 10,000 auctions deviates by less than 2% from the average price of the 10,000 auctions that were hold 100,000 rounds prior to the last 10,000 auctions[103]. However, for the *Uncertainty and Information Case*, we change the definition for a stable equilibrium as this case is more dynamic due to the varying demand. Therefore, stability of the equilibrium is defined by the stable formation of Q-values of the individual players.[104] As the players are exploring strategies at the beginning, we truncate the results of the majority of the auctions. The average prices presented in the following subsections take into account merely the last 10,000 auctions of each model run. Also, the term *average prices* always refers to the marginal price in UPAs and the volume weighted average price of accepted bids in DPAs across all 50 runs.

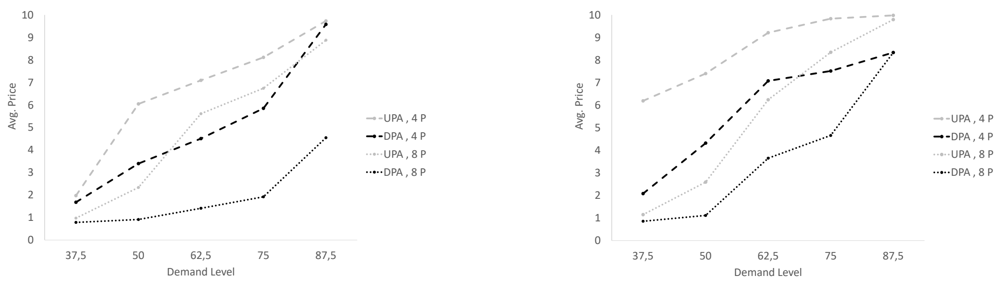
4.4.2 Base Case

We start by analysing the base case without uncertainty, i.e., both demand and supply are constant for all subsequent auctions of each model run. For this case, we will solely focus on the influence of the market clearing scheme given different settings with regard to the level of demand, the number and the symmetry in terms of size of participants. Aggregated supply is always set to 100. Hence, in the symmetric base case, there are 4 (or 8) identical players competing with a capacity of 25 (12.5) units each. Costs are set to zero for all players. Figure 4.2(a) illustrates the results for different levels of demand for 4 (dashed lines) and 8 (dotted lines) symmetric players. The uniform price scheme is indicated in grey, discriminatory pricing in black. Focussing on the influence of the number of players, we observe that – as expected – with a higher number of market participants prices decrease[105]. The opposite is true for the market demand: the higher the demand levels, the higher the market prices observed. At a demand level of 100 (demand to supply ratio of 1), prices always converge to the price cap of 10, hence this data point is not shown in any of the figures.

[103] As an example, if the average price of the successive auctions 390,001 to 400,000 deviate by less than 2% from the average price of auction rounds 290,001 to 300,000, the result is considered to be stable.

[104] Prices have been used as convergence criterion for the Base and Cost Case merely for the simplicity of the approach. Checking for convergence of the Q-values, as done in the Uncertainty and Information Case, would have yielded the same result.

[105] Some sample runs with less than 4 and more than 8 players clearly confirm this observation.



(a) symmetric players (b) asymmetric players

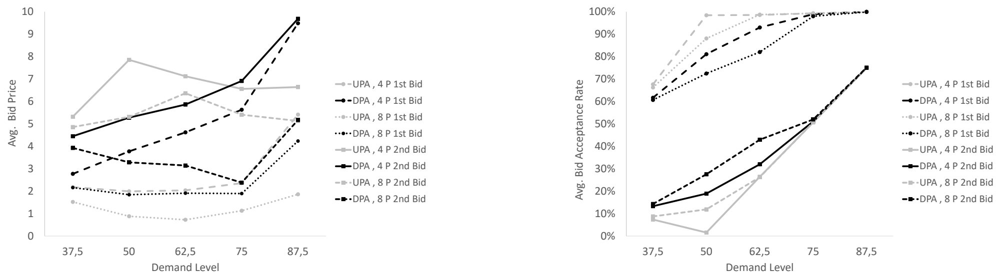
FIGURE 4.2: Avg. price in UPA and DPA with symmetric and asymmetric players

With regard to the market clearing scheme and focussing on the symmetric case (Figure 4.2(a)), we can observe generally higher prices in UPAs than in DPAs. This observation is independent from the number of market participants and the level of demand. Merely for low levels of demand at which prices are close to the price floor and high demand at which prices are close to the price cap, both auction types converge. The shape of the price increase from low to higher levels of demand indicates that strategic bidding is easier at an earlier stage in the case of UPAs. Especially in the market with 8 players, market prices with DPA remain closer to the price floor while UPAs prices have already increased. Regarding the market power of individual players, demand levels at which (in the symmetrical case all) players become pivotal[106] are at 75 for 4 and 87.5 for 8 players. In UPAs, the most rapid price increases can already be observed at demand levels without any pivotal player (between 37.5 and 50 for 4 and between 50 and 62.5 for 8 players). In case of DPA, the most rapid price increase occurs around the pivotal levels. Thus, players appear to be able to collaborate more easily with UPAs and can coordinate on higher prices even if capacity is hardly scarce.

A closer look into bidding strategies reveals some possible explanations for the price patterns observed. Comparing the individual average profits of the players, it can be noted that they hardly deviate from each other. The average standard deviation of observed profits is negligibly small. This is noteworthy as individual players have no information about other players' bidding strategies or realised profits, yet they find an equilibrium in which profits are nearly evenly distributed amongst them. Therefore, we consider average bid prices and acceptance rates of all players in the subsequent analysis on bidding strategies. In Figure 4.3(a), the average bid prices of the first and second bid are shown. The first bid is lower than or equal to the second bid by definition. It

[106]If a player is pivotal, demand cannot be covered without some capacity of this player. Hence, the barrier at which a player becomes pivotal serves as a measure of market concentration and indicates a potential for collusive behaviour.

is very obvious that the price spread between the first and second bid is much lower in DPAs when compared to UPAs, independent of the demand level. As derived by Krishna (2002), players in UPAs learn to heavily shade their bids and place the second bid significantly higher than the first one on average. This effect is less pronounced in DPAs, but still existing, which is an interesting finding by itself. Our data also reveals that the rate at which players bid both bids at the same price is twice as high for DPAs in the 4 player auctions (55 vs. 27%) and almost three times as high in the 8 player auctions (58 vs. 21%) across all demand levels.



(a) avg. bid prices

(b) avg. bid acceptance rates

FIGURE 4.3: Avg. bid prices and bid acceptance rates in UPA and DPA with symmetric players

The corresponding average bid acceptance rates of the first and second bid are displayed in Figure 4.3(b).[107] The bid acceptance rate is generally higher for the first and lower for the second bid in UPAs compared to DPAs. This seems plausible as players engage more aggressively in bid shading and the first bid potentially profits more from a high second bid, even if the acceptance rate of the second bid is very low. In the 4 player UPA case at a demand level of 50, the highest differential between first bid acceptance rate (98.4%) and second bid acceptance rate (1.6%) can be observed. At the very same observation point, the average difference between bid prices (see Figure 4.3(a)) reaches it maximum (first bid at 2.0, second bid at 7.9) and the average second bid price even its absolute maximum. As shown earlier in Figure 4.2(a), UPA prices rise steeply towards the demand level of 50 and the difference between UPA and DPA is at its maximum. For the 8 player case, the picture looks very similar at the demand level of 62.5. Hence, the higher UPA prices are a result of complex interactions between second bid acceptance rate and more aggressive bid shading.

[107]The bid acceptance rate shows which share of the capacity of the first and second bid is accepted on average.

As a first modification from our symmetric base case, we also consider the case of asymmetric players as shown in Figure 4.2(b). In our 4 player setting, one large player is endowed with half of the capacity, while the remaining 3 players are identical and own a capacity of one third of 50 each. In our 8 player setting, we have two large players are endowed with a capacity of 25 each, while the remaining 6 identical players merely own one sixth of 50 each. All other parameters remain unchanged. Generally, prices exceed those of the symmetric case[108]. This is to be expected as large players can exercise more market power than small players. Also, prices tend to rise faster towards the price cap at lower demand levels, at high demand levels the gradient of the price increase slows down. The general influence of the auction type remains unchanged, meaning that UPAs result in higher price levels than DPA independent from the level of demand. Demand levels at which the large player(s) become pivotal are at 50 for 4 and at 75 for 8 players.

In the asymmetric case, the analysis of the different bidding strategies of the large and small players is of particular interest. The average bid acceptance rates of the single large player (L) and the three small players (S) in the 4 player case[109] are displayed in Figure 4.4(a). At low and medium demand levels, the acceptance rates of the small players' first bids are much higher than those of the large player, the same is true for the second bids. In fact, the first bid acceptance rate of the small players at a demand level of 37.5 in the UPA case is already at 97.8% (large player at 46.1%). At a demand level of 75, the second bid acceptance rate of the small player is at 100%, while the second bid of the large player is not accepted at all. These differences are due to the fact that the large player places on average higher bids then the small players and takes the role of setting the marginal price. Our data shows that the large player is placing the marginal bid in more than 99.5% of all auctions for demand levels of 62.5 or higher for both auction types. The difference in bid acceptance rates is generally smaller in DPAs.

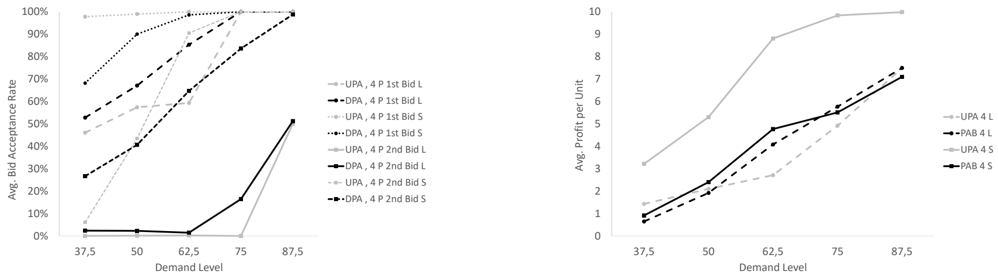
In UPAs, the small players learn to free ride on the high price setting of the large player. Hence, their profits per unit of capacity owned[110] are significantly higher than those of the large player for all demand levels (see Figure 4.4(b)). This is due to the fact that they earn the same marginal price for a higher share of their capacities. The distribution of profits looks quite different when it comes to DPAs, in which the differences in profits are much less pronounced. The small players still manage to secure higher bid acceptance rates, but this comes at the cost of bidding at lower prices. In fact, they maintain a considerable safety distance to the large players' bids in order for the large player not

[108]One exception is the 4 player DPA at a demand level of 87.5. An explanation is given at the end of this subsection.

[109]In this section, we focus on the 4 player case exclusively. While the results of the 8 player case are similar, they are less pronounced as there are two large players that have less market power than the single large player in the 4 player case.

[110]If a share of a players capacity is not sold, it is valued at a profit of zero.

to be tempted to underbid the small players. As this safety distance is particularly large at high demand levels (75 and 87.5), the large players' profit per unit of capacity owned even exceeds the average profits of the small players[111]. These findings confirm a statement by Kahn et al. (2001) who argue that smaller bidders are disadvantaged in DPAs as they are likely to benefit less from the exertion of market power by bigger players.



(a) avg. bid acceptance rates

(b) avg. profit per unit of capacity owned

FIGURE 4.4: Avg. bid acceptance rates and profits in UPA and DPA with 4 asymmetric players

4.4.3 Cost Case

In the base case above, capacity costs were set to zero. Now, we allocate different costs to the individual capacities of the individual players. Hence, this scenario additionally allows for analysing the efficiency of the competing auction types. In the context of our auction game, total welfare is at its maximum if costs are minimised. Hence, we define the 100% efficiency benchmark as an auction result in which only those bids that are associated to the lowest cost capacities have been awarded. As soon as one low capacity cost bid is not awarded and replaced by a higher capacity cost bid, the cost base increases to above 100% and the efficiency decreases accordingly.

		P1	P2	P3	P4	P5	P6	P7	P8
4 Player	Cost ascending (CA)	0/1	2/3	4/5	6/7				
	Cost mixed (CM)	0/7	1/6	2/5	3/4				
8 player	Cost ascending (CA)	0/0	1/1	2/2	3/3	4/4	5/5	6/6	7/7
	Cost mixed (CM)	0/7	0/7	1/6	1/6	2/5	2/5	3/4	3/4

TABLE 4.1: Cost allocation schemes among players (1st half of capacity/2nd half of capacity)

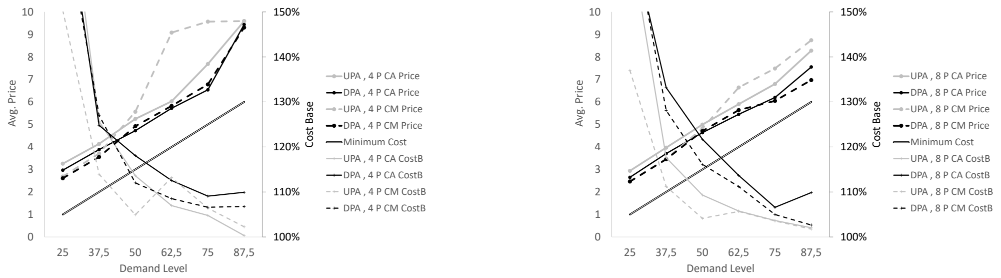
[111]This is also the reason for the single exception observed (4 player DPA, demand level of 87.5), at which prices of the symmetric case are higher than in the asymmetric case.

We conducted a wide range of trial runs with different cost allocations and found two main cases whose results show different characteristics. In the first set, costs are allocated in ascending order (cost scenario CA) as shown in Table 4.1. In the 4 player case, this translates into the first player having cost of zero allocated to one half of its capacity and costs of 1 to its other half, the second player having costs of 2 and 3 and so on. In the second case, costs are mixed among players (cost scenario CM). In the 4 player case, the first player is now endowed with cost of zero and 7, the second player with 1 and 6 and so on[112].

The results of the 4 player auction are displayed in Figure 4.5(a). In the ascending cost scenario (CA), prices increase mainly in parallel with the minimum cost. Only at a demand level of 75 for UPAs (87.5 for DPAs), the price increase accelerates. The price differences between UPA and DPA are small when compared to our zero cost case as displayed in Figure 4.2(a), but UPA prices again exceed those of DPAs for all demand levels. The corresponding cost base is generally decreasing (efficiency is increasing) with higher demand levels. There are two systematic reasons for this trend. First, the relative cost difference is higher at low cost (and low demand) levels even though the absolute cost difference between our costs steps is constant and amounts to 1[113]. Second, the higher the demand level, the less high-cost extra-marginal capacities are available that might potentially increase the cost base. At a demand level of 100 (not shown in the graphs), the cost base and efficiency are per definition at 100% as all capacities available are required to cover the demand. With regard to the auction types, the cost base of UPA is 4 to 10 percentage points lower when compared to DPA for demand levels of 50 or higher. Merely at low demand levels, UPAs feature a slightly higher cost base. Comparing the mixed cost scenario (CM) to CA reveals some remarkable differences, even though the overall costs and hence the minimum cost are the same. The modified allocation of costs leads to a steep increase of UPA prices at demand levels of 62.5 and 75, while DPA prices are very similar to CA scenarios and rise in parallel with the minimum cost for the most part. The price increase coincides with a sudden rise of the cost base. At a demand level of 62.5, the UPA cost base exceeds DPA by almost 5 percentage points, whereas UPA cost base is equal to DPA at a demand level of 75 and 5 to 23 percentage points lower than DPA for all other demand levels.

[112] We also conducted extensive runs for a mixed cost case in which the first player is endowed with capacity costs of zero and 4, the second player with 1 and 5 and so on. As the results are very similar to the CM scenario as shown in Table 4.1, we choose not to present the data here.

[113] As an example, if a low capacity cost bid (cost of 1) is replaced by the next higher bid (cost of 2), the cost base increases by 100%. If a bid with associated costs of 4 is replaced by the next higher bid (cost of 5), the cost base merely increases by 25%.



(a) 4 players

(b) 8 players

FIGURE 4.5: Avg. price and cost base in UPA and DPA with 4 and 8 players

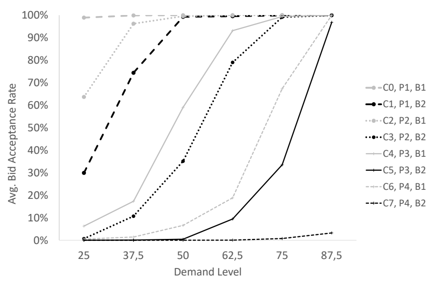
The results of the 8 player auction are shown in Figure 4.5(b). Again, prices in the CA scenario rise in parallel with the minimum cost, the UPA price increase at demand levels of 62.5 and 75 in the CM scenario is much less pronounced than in the 4 player case but still visible. The corresponding increase in the cost base is less steep as well. Therefore, UPA cost base remains below DPA for all demand levels by up to 34 percentage points. The same holds true for the CA scenarios, in which DPA cost base exceeds UPA by up to 16 percentage points.

Taking a closer look, we first explore why the UPA cost base is lower than DPA in most cases and second, why prices in the UPA CM scenario are significantly higher than in CA at demand levels of 62.5 and 75. The average bid acceptance rates of the 4 player auctions are shown in Figure 4.6. The subfigures are now arranged by the underlying capacity costs in order to put the competing cost allocation scenarios on a comparable basis[114]. The average bid acceptance rate in the UPA ascending cost CA scenario (see Figure 4.6(a)) displays an interesting pattern. Players learn to push in their first (low capacity cost) bid very aggressively, while they place their second bid at a price in between the next (higher capacity cost) players' first and second bid. Also, they rise the bid acceptance rate of their second bid close to 100% before the second next player is able to increase its first bid well above 20%. At a demand level of 50, the average first bid acceptance rate of the third player with underlying capacity costs of 4 (C4, P3, B1) is significantly higher (59%) than the second players' second bid (C3, P2, P2, 31%), while the rate of the first players' second bid (C1, P1, B2) is already above 99%. This pattern is true for all players and all demand levels. Low capacity cost players largely exclude higher cost players from the market (except of the first bid of the next player), which comes at the expense of relatively low UPA prices as seen in Figure 4.5(a) and

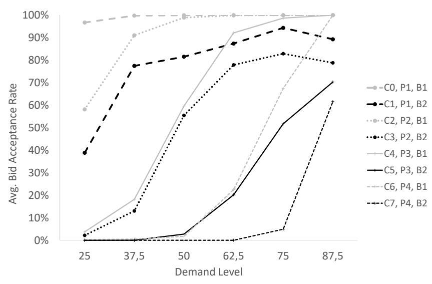
[114]For explanation: the first line in Figure 4.6(a) shows the first bid (B1) acceptance rate with underlying capacity cost of zero (C0) of player 1 (P1).

of a certain degree of inefficiency, as the higher cost first bids of the next player have higher acceptance rates than the previous players lower cost second bids.

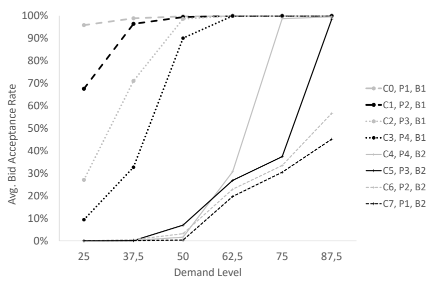
As shown in Figure 4.6(b), the pattern of the acceptance second bid rates looks quite different in the DPA CA scenarios. At demand levels of 50 or higher, the second bid acceptance rates of lower cost capacities are significantly lower, giving room to more costly capacities, while the first bid acceptance rates are only slightly lower than in UPA. At a demand level of 50, the average second bid acceptance rate of the first player (C1, P1, B2) is down from 99 to 82% when compared to UPA, while the rate of the second player (C3, P2, B2) is up from 35 to 56%. At this point, the first player sets the marginal bid in 76% and plays a same bid price strategy in 71% of all auctions. In UPAs on the other hand, the same player sets the marginal bid in only 6% of all auctions as the average second bid price is considerably lower (2.7 versus 4.8). In DPAs, low cost players cannot hide behind higher cost players by placing low bid prices, hence they are forced to play the same bid price strategy and set the marginal price more often. This ultimately results in a higher cost base (lower efficiency) for DPAs at demand levels of 50 or higher and for all demand levels in the 8 player case as shown in Figure 4.5(b).



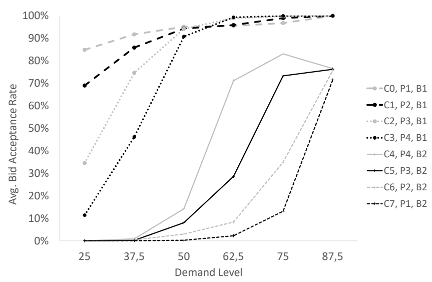
(a) UPA and ascending costs CA



(b) DPA and ascending costs CA



(c) UPA and mixed costs CM



(d) DPA and mixed costs CM

FIGURE 4.6: Avg. bid acceptance rates in UPA and DPA with 4 symmetric players for cost scenarios CA and CM

Due to the different allocation of costs, players modify their bidding strategies in the UPA CM scenarios as displayed in Figure 4.6(c). The acceptance rates of the 4 lowest capacity costs bids (C0 to C3), which are equivalent to the players first bids in CM, are decreasing as costs increase. The lowest cost bid features the highest acceptance rates, the second lowest the second highest acceptance rates and so on. As the difference of the first and second capacity is larger now, the strategy of pushing more expensive players entirely out of the market does not apply any more. At a demand level of 50, the 4 cheapest bids, which are sufficient to cover demand, posses a combined market share of 97% (as compared to 84% in UPA CA), which also explains the lower cost base of 105% (114% in UPA CA). However, at a demand level of 62.5, the pattern suddenly changes. The average acceptance rate of the next expensive capacity bid (C04, P4, B2) drops to 31% (as compared to 93% in UPA CA for bid (C04, P3, B1)) and the rates of the three most costly capacity bids rise to on average 23% (9% in UPA CA). As a consequence, the cost base rises to 113%, exceeding the cost of UPA CA (107%) and even the cost of DPA CM (109%). As the bidding strategy from UPA CA is not applicable any more, players learn to jointly rise their second bids. Even though efficiency decreases, this strategy pays off in terms of higher UPA prices and higher profits per player.

Finally, we compare the results above with those of the DPA CM scenarios as shown in Figure 4.6(d). At demand levels of 50 or lower, low capacity cost bids have on average lower acceptance rates than in UPA CM, resulting in a higher cost base. However, compared to DPA CA, the capacity cost allocation leads to a more distinct segregation, with the order of acceptance rates of individual capacities mostly in line with their underlying costs. Hence, the cost base is lower at demand levels of 50 or higher by 2 to 6 percentage points.

To sum up, the argument of Kahn et al. (2001) that efficiency in DPAs is worse compared to UPAs as some low cost bids might be rejected as bidders overestimate the market clearing price can only partly be confirmed by our results. We have shown several examples, in which the efficiency of UPAs is worse than in DPAs. This is particularly true for low supply to demand ratios and for certain cost allocations among the players. Plus, there seems to be a general misconception about efficiency in MUMB UPAs. As bidders engage in bid shading and increase prices of their second bids, UPA results are generally inefficient as well.

4.4.4 Uncertainty and Information Case

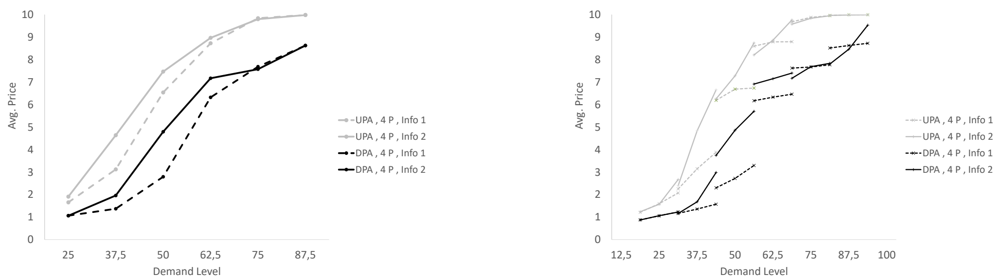
In this section, we start with our initial setting from section 4.4.2 in which all players have zero costs. We vary the market set-up in two ways: first, we introduce demand uncertainty, i.e., in each auction round, demand is randomly adjusted within the interval [-10;10] from the indicated average level of demand and demand changes from auction to auction are randomly chosen from $\{-1, 0, 1\}$.[115] Second, the market participants are provided with two different levels of information about the previous auction: either the demand of the previous auction is known (Info 2) or unknown (Info 1). If it is unknown (Info 1), players have to develop a bidding strategy not knowing the current level of demand, i.e., a strategy that maximises the expected profit for varying demand. In case demand of the previous auction is known, players still face the uncertainty of demand changes from one auction to the other within the range $\{-1, 0, 1\}$. However, knowing the previous demand reduces uncertainty about the demand in the next auction and gives and indication about scarcity in the market and whether a player might be pivotal or not.

We are aware of the fact that in most European balancing markets, the demand for balancing capacity is rather constant and the supply is varying instead. Even though one might think that it is irrelevant whether there is uncertainty about demand or supply, there are some structural differences. This is mainly due to the fact that if supply is varying, the individual players posses additional private information as they are aware of the change of their own supply. Hence, even in the Info 1 regime in which players do not know the total supply, they are aware of their own supply changes. The larger a player's capacity is, the more conclusions he can draw from its own to the total supply changes. This higher level of information in the Info 1 case diminishes the differential between the two information regimes. For this reason, we decided to show demand instead of supply variation in this section.

The results of the 4 player asymmetric case with one large player being endowed with half of the capacity and the remaining players with one third of 50 each is shown in Figure 4.7(a). We choose the asymmetric case as differences between the two info levels are much more pronounced compared to symmetric player case. As seen in the previous sections, UPA prices always exceed those of DPAs and prices rise with increasing demand. The effect of the information level on prices is significant around the pivotal demand level of the large player (37.5 to 62.5). If players know about the total demand of the previous auction (Info 2), prices exceed those of the Info 1 regime for both UPA and DPA. The difference between the two information regimes is largest at a demand level of 37.5 for UPAs and 50 for DPAs. However, at demand levels of 75 or higher the differential between the two information regimes becomes very small, with Info 1 prices even slightly exceeding those of Info 2.

[115] This restriction is important. If demand changes were completely random in the whole interval [-10;10], information about the previous demand would be entirely worthless.

A first explanation for the price pattern observed can be found in Figure 4.7(b). Here, each observation point of Figure 4.7(a) is further decomposed into three sub demand levels. For example, the average Info 2 UPA price at an average demand of 37.5 amounts to 4.6 (see Figure 4.7(a)). However, the actual underlying demand varies between 27.5 and 47.5. We divide this range into three parts of equal size and then report their average prices in Figure 4.7(b). In this case, the average price for low demand levels (interval [27.5;34.2]) amounts to 2.4, for medium demand levels [34.2;40.8] to 4.8 and for high demand [40.8;47.5] to 6.7. The Info 2 gradient of the price increase exceeds the one of Info 1 at all demand levels and for both auction types. This indicates that players use the additional information about the demand level of the previous auction to actively differentiate their bidding strategies, which is not possible in the Info 1 regime. This effect is largest around the pivotal demand level of 50 of the large player. However, at high average demand levels, Info 1 prices exceed those of Info 2 in the low demand sub-interval, as players in Info 2 actively push down prices while the slope of Info 1 is rather flat. This effect results in overall slightly higher Info 1 prices for demand levels of 75 or higher as seen in Figure 4.7(a).



(a) overview

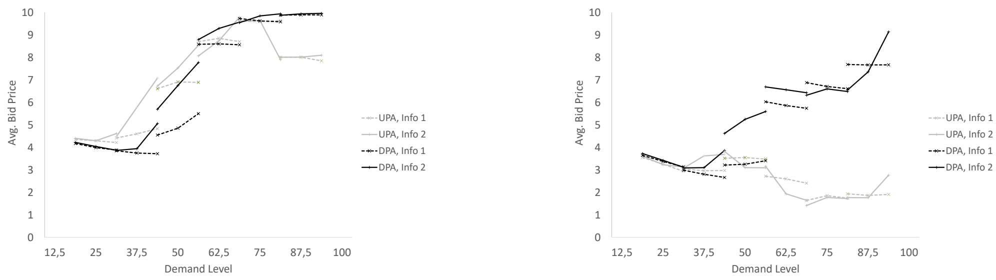
(b) grouped by demand level

FIGURE 4.7: Avg. price in UPA and DPA with demand uncertainty and information levels with 4 asymmetric players

As already assumed, the large player can be identified as the main driver for higher prices and steeper price gradients observed in the Info 2 regime. The average bid prices[116] of the large and small players are displayed in Figure 4.8. At average demand levels of 37.5 to 62.5, the large player aggressively differentiates its bidding strategy with respect to the sub demand levels (see Figure 4.8(a)). This is intuitive because if the large players know that he is pivotal, he can exploit this situation more strongly compared to the case in which he has to guess its strategic position (Info 1).

[116]To simplify the graphic, we show the combined average price of the first and second bid in Figure 4.8.

Small players on the other side exhibit different bidding strategies as displayed in Figure 4.8(b). In UPAs, average bid prices are significantly lower when compared to the large player and the differential between Info 1 and Info 2 is smaller as well. This is mainly due to the fact that small players free ride, independent of the information regime. In DPAs, differences compared to the large player are smaller, but absolute bid prices are still at a generally lower level. It is very interesting to observe, that the largest price increase in DPA Info 2 occurs at an average demand level of 87.5, the level at which the small players become pivotal.



(a) large player

(b) avg. of small players

Figure 4.8: Avg. bid prices in UPA and DPA with demand uncertainty and information levels with 4 asymmetric players

We choose to exclusively show the 4 player asymmetric case in this section which features the most significant differences between the information regimes. However, we have conducted several test runs with symmetric and with 8 players. In both cases, the price differentials between the two information regimes diminish. This is mainly due to an effect that we have observed in our 4 player asymmetric case at high demand levels of 62.5 and 75 (see Figure 4.7(a)). In the absence of a dominant player, players still actively differentiate their bidding strategies with Info 2. However, their higher prices in the high demand sub-interval are mostly offset by lower prices in the low demand subinterval when compared to the Info 1 prices. Hence, average prices turn out to be very similar.

4.5 Conclusion

In this paper, we develop an agent-based Q-learning model to simulate strategic bidding behaviour in repeated auctions under varying market clearing schemes. To our knowledge, we are the first to extend the Q-learning algorithm to a MUMB set-up.

In addition, we analyse the influence of uncertainty and different information regimes regarding previous auctions provided to the players. Our findings are manifold:

First, we find that with an increasing number of players and increasing supply to demand ratio prices are decreasing. This corresponds to common expectations and indicates reasonable bidding behaviour of the modelled players. Furthermore, we observe higher average prices under UPA than with DPA. This result is valid for all levels of demand and number of players. Uniform pricing seems to facilitate strategic bidding in repeated auctions even if the available supply significantly exceeds demand and no single player is pivotal. This is mainly due to the fact that players aggressively engage in bid shading by rising the price of their second bids as described by Krishna (2002). Even with low bid acceptance rates, their first bid can profit disproportionately from an elevated second bid. This is not the case in DPAs. Our analysis shows that the difference between the first and second bid is significantly smaller when compared to UPA and the same bid price strategy is applied more often. As the number of players increases and as prices approach the cap or the floor price, price differences between UPA and DPA diminish. With regard to asymmetric players, our findings confirm Kahn et al. (2001) who argue that smaller bidders are disadvantaged in DPAs as they are likely to benefit less from the exertion of market power by bigger players. In UPAs on the other side, small players can free ride on the large players' bidding strategy and obtain significantly higher profits per capacity owned.

Second, we compare the auction types with regard to their efficiency. We find, that the results are ambiguous and that the argument of Kahn et al. (2001) who claim that UPAs are always more efficient as in DPAs, some low cost bids might be rejected as bidders overestimate the market clearing price, cannot be confirmed. While in the majority of cases their statement can be confirmed, we have shown several examples in which the efficiency of UPAs is lower than in DPAs. This is particularly true for low demand to supply ratios and for certain cost allocations among the players. Our results indicate that the common expectations about efficiency of MUMB UPAs might not be generally true. As bidders engage in bid shading and increase prices of their second bids, UPA results are generally inefficient as well.

Third, we are able to analyse the influence of published information concerning previous auctions on average prices. For this purpose we introduce demand uncertainty in our model. Although the effect of providing more information about the demand level of previous auctions is ambiguous with symmetric players, prices tend to increase with asymmetric players with additional information. This is particularly true if the demand levels are close to the pivotal level of the large player. This is due to the fact that the large player aggressively differentiates its bidding strategy with respect to the sub demand levels as he knows whether he is pivotal or not. Without additional information, the large player bids at lower prices as he has to guess its strategic position. Again, differences get smaller when supply to demand ratios, the number of players or symmetry among players increases.

Based on our simulation results we conclude the following: For markets with many participants and limited market concentration, UPAs may be favourable compared to DPAs even though they might result in slightly increased market prices. Typical issues with DPAs can be avoided when choosing UPAs. With UPAs, players have lower transaction costs (in DPAs they need to forecast the marginal price) and smaller players are disadvantaged as they benefit less from the exertion of market power by bigger players. This also leads to the fact that market entry of new players is less likely. Plus in general, efficiency of UPAs is higher, especially if there are many symmetric players.

Concerning markets with a small number of players and potentially few large players – which might be the case in some balancing markets – our results indicate that DPAs are advisable if low prices are the main objective. They limit the potential for the exertion of market power and result in lower average market prices. The publishing of previous supply to demand rations should also be handled with care, as our results indicate that additional information may facilitate strategic bidding behaviour. Coming back to our introductory example concerning the changes in the German balancing markets, our analysis provides some support to the choice by BNetzA not to disclose information about the supply to demand ratio of past auctions. However, as the number of players increases[117] and pivotal players disappear, a switch to UPA may be advisable and the amount of information about past auction results should be increased.

[117]See Viehmann (2017) for the recent development of the number of balancing capacity providers in Germany.

Appendix

Proof of Proposition 3.2

To show that q is an equilibrium, we choose the smallest number $k \in N$ so that $q_k(\omega_k, \omega_{-k}) < \omega_k$. Then $q_k(\omega_k, \omega_{-k})$ is firm k's best response by definition. Since a firm $i > k$ minimizes the same payoff function as firm k does, $q_i(\omega_i, \omega_{-i}) = q_k(\omega_k, \omega_{-k})$ is the best response of firm i as well. Any firm $i < k$ can not increase its output and does not have an incentive to decrease its output because $q_i(\omega_i, \omega_{-i}) < q_k(\omega_k, \omega_{-k})$. Furthermore, firm k does not have an incentive to decrease its output.

To show that the equilibrium is unique, we consider $\tilde{q} \neq q$ to be another equilibrium and denote i as the smallest number such that

$$\tilde{q}_i(\omega_i, \omega_{-i}) \neq q_i(\omega_i, \omega_{-i}).$$

Without loss of generality, we assume that $i = 1$. First, we consider the case in which

$$\tilde{q}_1(\omega_1, \omega_{-1}) < q_1(\omega_1, \omega_{-1}).$$

This implies

$$\tilde{q}_1(\omega_1, \omega_{-1}) < \omega_1,$$

which in turn leads to

$$\tilde{q}_j(\omega_j, \omega_{-j}) = \tilde{q}_j(\omega_i, \omega_{-i})$$

for all $j > i$. But then

$$q^C = \tilde{q}_1(\omega_1, \omega_{-1}) < q_1(\omega_1, \omega_{-1}),$$

contradicting (3.4).

Second, when

$$\tilde{q}_1(\omega_1, \omega_{-1}) > q_1(\omega_1, \omega_{-1}),$$

we conclude

$$q_1(\omega_1, \omega_{-1}) < \omega_1$$

and thus

$$q_j(\omega_j, \omega_{-j}) = q_i(\omega_i, \omega_{-i})$$

for all $j > i$, meaning that q is the standard form of the Cournot oligopoly equilibrium, which is unique, thus implying that $\tilde{q}$ can not be an equilibrium.

To show that the statement holds in the case of duopoly, we let r denote the best response function of the unrestricted Cournot duopoly. We choose $\omega \in \Omega$ arbitrarily and assume that firm 1 produces ω_1 and firm 2 produces $r(\omega_1) < \omega_2$ in the unique equilibrium. Then, since $r(q^C) = q^C$,

$$\omega_1 + r(\omega_1) \leq 2r(q^C)$$

if and only if

$$r(\omega_1) \leq 2q^C - \omega_1,$$

which is equivalent to

$$r(\omega_1) - r(q^C) \leq q^C - \omega_1. \tag{4.4}$$

The decrease of production by firm 1 must overcompensate the increase of production by firm 2, which is true: Equation (4.4) holds because $r' > -1$. Without loss of generality, we assume that $\mu\left(T_1 < q^C\right) > 0$, which yields the given statement.

The result easily translates to the case of an oligopoly. We arbitrarily choose a capacity configuration $(\omega_1, \omega_2, \ldots, \omega_n)$. Again, we assume that $\omega_i \leq \omega_j$ if $i \leq j$. Choose k so that $q(\omega_{k-1}, \omega_{-k-1}) = \omega_{k-1}$ and $q(\omega_k, \omega_{-k}) < \omega_k$. Define the capacity configuration $(\tilde{\omega}_1, \tilde{\omega}_2, \ldots, \tilde{\omega}_n)$ by $\tilde{\omega}_i := \omega_i$ if $i < k-1$ and for $i \geq k-1$ choose $\tilde{\omega}_i$ large enough so that in the corresponding equilibrium $q(\omega_{k-1}, \omega_{-k-1}) = \omega_{k-1} < \tilde{\omega}_{k-1}$, meaning that when moving from $(\omega_1, \omega_2, \ldots, \omega_n)$ to $(\tilde{\omega}_1, \tilde{\omega}_2, \ldots, \tilde{\omega}_n)$ the former active capacity restriction of firm $k-1$ becomes inactive, whereas all other active capacity restrictions remain as they are. Having established this, it is sufficient to show that the total output of the industry with respect to the former capacity configuration is smaller than the output of the industry with respect to the new capacity configuration $(\tilde{\omega}_1, \tilde{\omega}_2, \ldots, \tilde{\omega}_n)$. But this follows from the case of duopoly: We can either focus on the residual game in which we neglect firms $1, 2, \ldots, k-2$ or we assume without loss of generality that $k = 2$.

Proof of Theorem 1

Any feasible strategy profile q is an element of

$$S = \prod_{j \in N} \{q : T \to \mathbb{R}_+ | q(t) \leq t \text{ for all } t \in T\}.$$

If we define

$$d(q, q') = \max_{j \in N, t \in T} |q_j(t) - q'_j(t)|,$$

then (S, d) is a complete metric space. Thus, it is sufficient to show that $\tilde{r}$ is a contraction with respect to d, since then Banach's fixed-point theorem establishes that $\tilde{r}$ has a unique fixed point. Therefore, it remains to be shown that there exists $0 \leq \theta < 1$ so that

$$d(\tilde{r}(q), \tilde{r}(q')) \leq \theta d(q, q')$$

for every $q' \in S$ such that $q' \neq q$.

We define

$$p := \min_{t \in T} \{\mu (T_2 = 0 | T_1 = t)\}$$

and

$$\theta := \frac{(1-p)(j-1)}{2}.$$

Clearly, if $j = 2$, then $\theta < 1$. If $j = 3$, then $p > 0$ due to (3.6) and thus $\theta < 1$ as well. We choose $s \in T$ and $i \in N$ such that

$$\begin{aligned} d(\tilde{r}(q), \tilde{r}(q')) =& |\tilde{r}_i(s, q_{-i}) - \tilde{r}_i(s, q'_{-i})| \\ =& \left|\min\left\{s, r\left(E\left[q_{-i}|T_i = s\right]\right)\right\} - \min\left\{s, r\left(E\left[q'_{-i}|T_i = s\right]\right)\right\}\right|. \end{aligned} \tag{4.5}$$

If (4.5) $= 0$, then $q = q'$, which contradicts the assumption that $q \neq q'$. Thus, we must have (4.5) > 0. In particular, either

$$r\left(E\left[q_{-i}|T_i = s\right]\right) < s$$

or

$$r\left(E\left[q'_{-i}|T_i = s\right]\right) < s$$

or both. For the last case when both capacity limits are not active, we obtain

$$(4.5) = \frac{1}{2}\left|E\left[q_{-i} - q'_{-i}|T_i = s\right]\right| \leq \frac{(1-p)(j-1)}{2} d(q, q') = \theta d(q, q'),$$

since q_{-i} and q'_{-i} differ at most with probability $1-p$, and the difference can never exceed $(j-1)d(q, q')$ by definition. If only one capacity constraint is active, say $r\left(E\left[q_{-i}|T_i = s\right]\right) = s$ without loss of generality, we get

$$\begin{aligned} (4.5) =& s - r\left(E\left[q'_{-i}|T_i = s\right]\right) \\ \leq& r\left(E\left[q_{-i}|T_i = s\right]\right) - r\left(E\left[q'_{-i}|T_i = s\right]\right) \end{aligned}$$

and the proposed statement follows from the case case where both capacity limits are not active.

Bibliography

Bakirtzis, A., Tellidou, A., 2006. Agent-Based Simulation of Power Markets under Uniform and Pay-as-Bid Pricing Rules using Reinforcement Learning. IEEE PES Power System Conference and Exposition.

Barth, R., Weber, C., Swider, D., 2008. Distribution of costs induced by the integration of RES-E power. Energy Policy 36 (8), 3107–3115.

Belmans, R., Deuse, J., Meeus, L., Purchala, K., Stubbe, M., Vandezande, L., 2009. Study on interaction and dependencies of balancing markets, intraday trade and automatically activated reserves. Tech. rep., Tractebel Engineering and Katholieke Universiteit Leuven (KUL).

Benth, F., Cartea, ., Kiesl, R., 2008. Pricing forward contracts in power markets by the certainty equivalence principle: Explaining the sign of the market risk premium. Journal of Banking & Finance 32 (10), 2006–2021.

Bergh, K. V. d., Boury, J., Delarue, E., July 2015. The Flow-Based Market Coupling in Central Western Europe: concepts and definitions. TME WORKING PAPER - Energy and Environment - WP EN2015-13.

Bessembinder, H., Lemmon, M., 2002. Equilibrium Pricing and Optimal Hedging in Electricity Forward Markets. Journal of Finance 57 (3), 1347–1382.

Bierbrauer, M., Menn, C., Rachev, S. T., Trück, S., 2007. Spot and derivative pricing in the EEX power market. Journal of Banking & Finance 31 (11), 3462–3485.

Bischi, G., Chiarella, C., Kopel, M., Szidarovszky, F., 2010. Nonlinear Oligopolies. Stability and Bifurcations, 1st Edition. Springer Verlag.

BMWi, October 2014. Ein Strommarkt für die Energiewende - Diskussionspapier des Bundesministeriums für Wirtschaft und Energie (Grünbuch). Tech. rep., Bundesministerium für Wirtschaft und Energie.

BNetzA, 2010. Monitoringbericht 2010. Tech. rep., Bundesnetzagentur.

BNetzA, April 2011. Beschluss in dem Verwaltungsverfahren wegen der Festlegung zu Verfahren zur Ausschreibung von Regelenergie in Gestalt der Sekundärregelung, Az: BK6-10-098.

BNetzA, 2012a. Beschluss in dem Verwaltungsverfahren den Ausgleichsenergiepreis-Abrechungssystems vom 25.10.2012, Az: BK6-12-024. Tech. rep., Bundesnetzagentur.

BNetzA, 2012b. Modell zur Berechnung des regelzonenübergreifenden einheitlichen Bilanzausgleichsenergiepreises (reBAP) unter Beachtung des Beschlusses BK6-12-024 der Bundesnetzagentur vom 25.10.2012. Tech. rep., Bundesnetzagentur.

BNetzA, December 2015. Quartalsbericht zu Netz- und Systemsicherheitsmassnahmen - Erstes und zweites Quartal 2015. Tech. rep., Bundesnetzagentur.

BNetzA, August 2016. 3. Quartalsbericht 2015 zu Netz- und Systemsicherheitsmaßnahmen - Viertes Quartal 2015 sowie Gesamtjahresbetrachtung 2015. Tech. rep., Bundesnetzagentur.

Boogert, A., Dupont, D., 2005. On the effectiveness of the anti-gaming policy between the day-ahead and real-time electricity markets in The Netherlands. Energy Economics 27 (5), 752–770.

Borchert, J., Schemm, R., Korth, S., 2006. Borchert, J., Schemm, R., Korth, W., 2006. Stromhandel. Institutionen, Marktmodelle, Pricing und Risikomanagement. Schäffer-Poeschel Verlag, Stuttgart. Schäffer-Poeschel Verlag, Stuttgart.

Botterud, A., Kristiansen, T., Ilic, M. D., 2010. The relationship between spot and futures prices in the Nord Pool electricity market. Energy Economics 32 (5), 967–978.

Bower, J., Bunn, D., 2001. Experimental analysis of the efficiency of uniform-price versus discriminatory auctions in the England and Wales electricity market. Journal of Economic Dynamics & Control 25 (3-4), 561–592.

Brunekreeft, G., Neuhoff, K., Newbery, D., 2005. Electricity transmission: An overview of the current debate. Utilities Policy 13 (2), 73–92.

Budish, E., Cramton, P., Shim, J., 2014. Implementation Details for Frequent Batch Auctions: Slowing Down Markets to the Blink of an Eye. American Economic Review 104 (5), 418–424.

Bundeskartellamt, January 2011. Sektoruntersuchung Stromerzeugung und -großhandel - Abschlussbericht gemäß § 32e GWB . Tech. rep., Bundeskartellamt. URL `http://www.bundeskartellamt.de/SharedDocs/Publikation/DE/Sektoruntersuchungen/Sektoruntersuchung%20Stromerzeugung%`

20Stromgrosshandel%20-%20Abschlussbericht.pdf?__blob=publicationFile&v=3

Bundeskartellamt, May 2015. Fallbericht - Oberlandesgericht Düsseldorf bestätigt Kartellrechtswidrigkeit der Entgeltregelung der "Irsching-Verträge". Tech. rep., Bundeskartellamt.
URL http://www.bundeskartellamt.de/SharedDocs/Entscheidung/DE/Fallberichte/Kartellverbot/2015/B8-78-13.pdf?__blob=publicationFile&v=2

Bunn, D., Zachmann, G., 2010. Inefficient Arbitrage in Inter-Regional Electricity Transmission. Journal of Regulatory Economics 37 (3), 243–265.

Bunn, D. W., Oliveira, F., 2007. Agent-based analysis of technological diversification and specialication in electricity markets. European Journal of Operational Research 181 (3), 1265–1278.

Burstedde, B., 2012. Essays on the Economics of Congestion Management - Theory and Model-based Analysis for Central Western Europe. Ph.D. thesis, Universität zu Köln.

BWE, 2009. Bundesverband windenergie e.v. http://www.wind-energie.de.

Chao, H.-P., Wilson, R., 2002. Multi-Dimensional Procurement Auctions for Power Reserves: Robust Incentive-Compatible Scoring and Settlement Rules. Journal of Regulatory Economics 22 (2), 161–183.

Cramton, P., Stoft, S., 2008. Forward reliability markets: Less risk, less market power, more efficiency. Utilities Policy 16 (3), 194–201.

Daskalakis, G., Markellos, R. N., 2009. Are electricity risk premia affected by emission allowance prices? Evidence from the EEX, Nord Pool and Powernext. Energy Policy 37 (7), 2594–2604.

Dieckmann, B., 2008. Engpassmanagement im Europäischen Strommarkt. Ph.D. thesis, Westfälische Wilhelms-Universität Münster.

Douglas, S., Popova, J., 2008. Storage and the electricity forward premium. Energy Economics 30 (4), 1712–1727.

Egerer, J., Hirschhausen, C. v., Weibezahn, J., Kemfert, C., February 2015. Energiewende und Strommarktdesign: Zwei Preiszonen für Deutschland sind keine Lösung. DIW Wochenbericht Nr. 9/2015.

Einy, E., Haimanko, O., Moreno, D., Shitovitz, B., 2010. On the Existence of Bayesian Cournot Equilibrium. Games and Economic Behavior 68 (1), 77–94.

Einy, E., Moreno, D., Shitovitz, B., 2002. Information Advantage in Cournot Oligopoliy. Journal of Economic Theory 106 (1), 151–160.

ENTSO-E, 29th of May 2013a. Entso-e draft network code on electricity balancing. Version 1.22.

ENTSO-E, 2013b. European Network of Transmission System Operators for Electricity. Data downloaded on the 6th of January 2013. Website: www.entsoe.net.

ENTSO-E, August 2014. ENTSO-E Network Code on Electricity Balancing. Version 3.0.
URL https://www.entsoe.eu/Documents/Network%20codes%20documents/NC%20EB/140806_NCEB_Resubmission_to_ACER_v.03.PDF

ENTSO-E, January 2016. XBID Cross-Border Intraday Market Project - 3rd User Group Meeting.
URL https://www.epexspot.com/document/34618/User%20Group%20meeting%20-%2017%20February%202016%20-%20Presentation

ENTSO-E, May 2017a. Consultation Report "FCR Cooperation".
URL https://www.entsoe.eu/Documents/Consultations/20170601_FCR_Consultation_Report.pdf

ENTSO-E, Mar. 2017b. ENTSO-E Network Code on Electricity Balancing.
URL https://www.entsoe.eu/Documents/Network%20codes%20documents/NC%20EB/Informal_Service_Level_EBGL_16-03-2017_Final.pdf

ENTSO-E, Mar. 2017. Survey on Ancillary Services Procurement, Balancing Market Design 2016.
URL https://www.entsoe.eu/Documents/Publications/Market%20Committee%20publications/WGAS_Survey_final_10.03.2017.pdf

EPEX, 2013. European Power Exchange. Data downloaded on the 8th of January 2013. Website: www.epexspot.com.

EPEX Spot, GME, Nord pool, OMIE, OPCOM, OTE, TGE, January 2016. EUPHEMIA Public Description - PCR Market Coupling Algorithm. Tech. rep., EPEX Spot, GME, Nord pool, OMIE, OPCOM, OTE, TGE.
URL https://www.epexspot.com/document/34460/Euphemia%3A%20Public%20documentation%20-%20January%202016

European Commission, 2007. DG Competition Report On Energy Sector Inquiry.

European Commission, 2009. Draft discussion paper by DG TREN on transparency and integrity of traded wholesale markets in electricity and gas. . Tech. rep., European Commission.
URL http://ec.europa.eu/energy/gas_electricity/consultations/doc/2010_07_23/discussion_paper_on_market_integrity_and_transparency.pdf

European Union, Directive 54/EC, 2003. Directive 2003/54/EC concerning common rules for the internal market in electricity and repealing Directive 96/92/EC.

European Union, Regulation EC No 1228, 2003. Regulation (EC) No 1228/2003 on conditions for the access to the network for cross-border exchanges in electricity.

Fabra, N., Fehr, N.-H. v. d., Harbord, D., 2006. Designing electricity auctions. RAND Journal of Economics 37 (1), 23–46.

Fama, E. F., French, K. R., 1987. Commodity Futures Prices: Some Evidence on Forecast Power, Premiums, and the Theory of Storage. The Journal of Business 60 (1), 55–73.

Flinkerbusch, K., Heuterkes, M., 2010. Cost reduction potentials in the German market for balancing power. Energy Policy 38 (8), 4712–4718.

Frederico, G., Rahman, D., 2003. Bidding in an electricity pay-as-bid auction. Jounal of Regulatory Economics 24 (2), 175–211.

Garcia, R. C., Contreras, J., van Akkeren, M., Garcia, J. B. C., 2005. A GARCH forecasting model to predict day-ahead electricity prices. IEEE Transactions on Power Systems 20 (2), 867–874.

Geanakoplos, J., Robert, A., Farmer, J. D., Howitt, P., Conlee, B., Goldstein, J., Hendrey, M., Palmer, N., Yang, C.-Y., 2012. Getting at systemic risk via an agent-based model of the housing market. American Economic Review 102 (3), 53–58.

Gebhardt, G., Höffler, F., 2013. How competitive is cross-border trade of electricity? Theory and evidence from European electricity markets. The Energy Journal 34 (1), 125–154.

Graf, C., Wozabal, D., 2013. Measuring competitiveness of the EPEX spot market for electricity. Energy Policy 62, 948–958.

Grimm, V., Ockenfels, A., Zoettl, G., 2008. Strommarktdesign: Zur Ausgestaltung der Auktionsregeln an der EEX. Zeitschrift für Energiewirtschaft 32 (3), 147–161.

Growitsch, C., Höffler, F., Wissner, M., 2010. Marktkonzentration und Marktmachtanalyse für den deutschen Regelenergiemarkt. Zeitschrift für Energiewirtschaft 34 (3), 209–222.

Hadsell, L., Shawky, H. A., 2007. One-day forward premiums and the impact of virtual bidding on the New York wholesale electricity market using hourly data. The Journal of Futures Markets 27 (11), 1107–1125.

Hailu, A., Thoyer, S., 2007. Designing Multi-unit Multiple-Bid Auctions: An Agent-based Computational Model of Uniform, Discriminatory and Generalised Vickrey Auctions. The Economic Record 83 (1), 57–72.

Harsanyi, J., 1967-69. Games with Incomplete Information Played by Bayesian Players. Management Science 14, 159–182, 320–334 and 486–502.

Heim, S., Götz, G., 2013. Do Pay-as-Bid Auctions Favor Collusion? Evidence from Germany's Market for Reserve Power. ZEW Discussion Papers No. 13-035 No. 13-035.

Huisman, R., Huurman, C., Mahieu, R., 2007. Hourly electricity prices in day-ahead markets. Energy Economics 29 (2), 240–248.

Jullien, C., Pignonb, V., Robinc, S., Starpolid, C., 2012. Coordinating Cross-Border Congestion Management Through Auctions: An Experimental Approach to European Solutions. Energy Economics 34 (1), 1–13.

Just, S., Weber, C., 2015. Strategic behavior in the German balancing energy mechanism: incentives, evidence, costs and solutions. Journal of Regulatory Economics 48 (2), 218–243.

Kahn, A. E., Cramton, P. C., Porter, R. H., Tabors, R. D., 2001. Uniform Pricing or Pay-as-Bid Pricing: A Dilemma for California and Beyond. The Electricity Journal 14 (6), 70–79.

Kimbrough, S. O., Murphy, F. H., 2013. Strategic bidding of offer curves: An agent-based approach to exploring supply curve equilibria. European Journal of Operational Research 229 (1), 165–178.

Knaut, A., Obermüller, F., Weiser, F., January 2017. Tender Frequency and Market Concentration in Balancing Power Markets. EWI Working Paper No 17/04.

Knaut, A., Paschmann, M., January 2017. Price Volatility in Commodity Markets with Restricted Participation. EWI Working Paper No 17/02.

Krishna, V., 2002. Auction Theory. Elsevier Science (USA).

Kristiansen, T., 2007. Cross-Border Transmission Capacity Allocation Mechanisms in South East Europe. Energy Policy 35 (9), 4611–4622.

Kutschinski, E., Uthmann, T., Polani, D., 2003. Learning competitive pricing strategies by multi-agent reinforcement learning. Journal of Economic Dynamics & Control 27 (11-12), 2207–2218.

Lise, W., Hobbs, B. R., Hers, S., 2008. Market power in the European electricity market—The impacts of dry weather and additional transmission capacity. Energy Policy 36 (4), 1331–1343.

London Economics, 2007. Structure and Performance of Six European Wholesale Electricity Markets in 2003, 2004 and 2005 - Study for the European Commission. Tech. rep., London Economics, Global Energy Decisions.

Longstaff, F. A., Wang, A. W., 2004. Electricity Forward Prices: A High-Frequency Empirical Analysis. The Journal of Finance LIX (4), 1877–1900.

Lucia, J. J., Torró, H., 2008. Short-term electricity futures prices: Evidence on the time-varying risk premium. IVIE Working Paper WP-EC 2008-08.

Madania, M., Van Vyve, M., 2015. Computationally efficient MIP formulation and algorithms for European day-ahead electricity market auctions. European Journal of Operational Research 242 (2), 580–593.

Maleug, D. A., Tsutsui, S. O., 1998. Oligopoly Information Exchange when Non-negative Prices and Output Constraints may Bind. Australian Economic Papers 37 (4), 363–371.

Meeus, L., 2011a. Implicit auctioning on the Kontek Cable: Third time lucky? Energy Economics 33 (3), 413–418.

Meeus, L., 2011b. Why (and how) to regulate power exchanges in the EU market integration context? Energy Policy 39 (3), 1470–1475.

Meeus, L., Verhaegen, K., Belmans, R., 2009. Block order restrictions in combinatorial electric energy auctions. European Journal of Operational Research 196 (3), 1202–1206.

Milstein, I., Tishler, A., 2015. Can price volatility enhance market power? The case of renewable technologies in competitive electricity markets. Resource and Energy Economics 41, 70–90.

Möller, C., Rachev, S. T., Fabozzi, F. J., 2011. Balancing energy strategies in electricity portfolio management. Energy Economics 33 (1), 2–11.

Müsgens, F., 2006. Quantifying market power in the German wholesale electricity market using a dynamic multi-regional dispatch model. The Journal of Industrial Economics 54 (4), 471–498.

Müsgens, F., Ockenfels, A., 2011. Design von Informationsfeedback in Regelenergiemärkten. Zeitschrift für Energiewirtschaft 35 (4), 249–256.

Müsgens, F., Ockenfels, A., Peek, M., 2012. Balancing Power Markets in Germany: Timing Matters. Zeitschrift für Energiewirtschaft 36 (1), 1–7.

Müsgens, F., Ockenfels, A., Peek, M., 2014. Economics and design of balancing power markets in Germany. Electrical Power and Energy Systems 55, 392–401.

Muche, T., 2014. Optimal operation and forecasting policy for pump storage plants in day-ahead markets. Applied Energy 113, 1089–1099.

Naghibi-Sistani, M. B., Akbarzadeh-Tootoonchi, M. R., Javidi-Dashte Bayaz, M. H., Rajabi-Mashhadi, H., 2006. Application of Q-learning with temperature variation for bidding strategies in market based power systems. Energy Conversion & Management 47 (11-12), 1529–1538.

Neuhoff, K., Ritter, N., Salah-Abou-El-Enien, A., Vassilopoulos, P., 2016. Intraday Markets for Power: Discretizing the Continuous Trading? DIW Discussion Papers 1544.

Nicolosi, M., 2010. Wind power integration and power system flexibility - An empirical analysis of extreme events in Germany under the new negative price regime. Energy Policy 38 (11), 7257–7268.

Nüssler, A., 2012. Congestion and redispatch in Germany - A model-based analysis of the development of redispatch. Ph.D. thesis, Universität zu Köln.

Ockenfels, A., 2007. Marktmachtmessung im deutschen Strommarkt in Theorie und Praxis - Kritische Anmerkungen zur London Economics-Studie. Energiewirtschaftliche Tagesfragen 9, 12–29.

Pirrong, C., Jermakyan, M., 2008. The price of power: The valuation of power and weather derivatives. Journal of Banking & Finance 32 (12), 2520–2529.

R Development Core Team, 2009. R: A language and Environment for Statistical Computing. http://www.R-project.org.

Rademaekers, K., Slingenberg, A., Morsy, S., 2008. Review and analysis of EU wholesale energy markets – Historical and current data analysis of EU wholesale electricity, gas and CO2 markets. ECORYS Nederland BV, Rotterdamm.

Raith, M., 1996. A General Model of Information Sharing in Oligopoly. Journal of Economic Theory 71 (1), 260–288.

Rassenti, S., Smith, L., Wilson, B., 2003. Discriminatory Price Auctions in Electricity Markets: Low Volatitly at the Expence of High Price Levels. Journal of Regulatory Economics 23 (2), 109–123.

Redl, C., Haas, R., Huber, C., Böhm, B., 2009. Price formation in electricity forward markets and the relevance of systematic forecast errors. Energy Economics 31 (3), 356–364.

Regelleistung.net, January 2016. Information zum Netzregelverbund und der internationalen Weiterentwicklung - Beitritt Frankreich (RTE) zum Internationalen Netzregelverbund (IGCC – International Grid Control Cooperation) - 15.01.20116. Tech. rep., German TSOs.

Richter, J., 2013. Incomplete Information in Cournot Oligopoly: The Case of Unknown Production Capacities. EWI Working Paper No 13/01.

Richter, J., Viehmann, J., 2014. The value of information in explicit cross-border capacity auction regimes in electricity markets. Energy Policy 70, 74–84.

Routledge, B. R., Seppi, D., Spatt, C., 2000. Equilibrium Forward curves for commodities. Journal of Finance 55 (3), 1297–1338.

Sensfuß, F., Ragwitz, M., Genoese, M., 2008. The merit-order effect: A detailed analysis of the price effect of renewable electricity generation on spot market prices in Germany. Energy Policy 36 (8), 3086–3094.

Shapiro, C., 1986. Exchange of Cost Information in Oligopoly. Review of Economic Studies 53 (3), 433–446.

Smith, C. W., Stulz, R. M., 1985. The Determinants of Firms' Hedging Policies. Journal of Financial and Quantitative Analysis 20 (4), 391–405.

Swider, D., 2007. Efficient Scoring-Rule in Multipart Procurement Auctions for Power Systems Reserve. IEEE Transactions on Power Systems 22 (4), 1717–1725.

Swider, D. J., Weber, C., 2007a. Bidding under price uncertaity in multi-unit pay-as-bid procurement auctions for power systems reserve. European Journal of Operational Research 181 (3), 1297–1308.

Swider, D. J., Weber, C., 2007b. Extended ARMA models for estimating price developments on day-ahead electricity markets. Electric Power Systems Research 77 (5-6), 583–593.

Trepper, K., Bucksteeg, M., Weber, C., 2015. Market splitting in Germany - New evidence from a three-stage numerical model of Europe. Energy Policy 87, 199–215.

Turvey, R., 2006. Interconnector Economics. Energy Policy 34 (13), 1457–1472.

UCTE, 2008. Union for the co-ordination of transmission of electricity. Data source: http://www.ucte.org/resources/dataportal.

Valitov, N., 2018. Risk premia in the German day-ahead electricity market revisited: The impact of negative prices. Energy Economics In press, Corrected Proof (https://doi.org/10.1016/j.eneco.2018.01.020).

Van Vyve, M., 2011. Linear prices for non-convex electricity markets: models and algorithms. CORE Discussion Paper 50.

Vandezande, L., Meeus, L., Belmans, R., Saguan, M., Glachant, J.-M., 2010. Well-functioning balancing markets: A prerequisit for wind power integration. Energy Policy 38 (7), 3146–3154.

Vickrey, W., 1961. Counterspeculation, Auctions, and Competitive Sealed Tenders. The Journal of Finance 16 (1), 8–37.

Viehmann, J., 2011. Risk Premiums in the German Day-Ahead Electricity Market. Energy Policy 39 (1), 386–394.

Viehmann, J., 2017. State of the German Short-Term Power Market. Zeitschrift für Energiewirtschaft 41 (2), 87–103.

Viehmann, J., Sämisch, H., 2009. Windenergieintegration bei negativen Strompreisen. Energiewirtschaftliche Tagesfragen 59, 49–51.

Waltman, U., Kaymak, U., 2008. Q-learning agents in a Cournot oilgopoly model. Journal of Economic Dynamics & Control 32 (10), 3275–3293.

Weber, A., Graeber, D., Semmig, A., 2010. Market Coupling and the CWE Project. Zeitschrift für Energiewirtschaft 34 (4), 303–309.

Weber, C., Vogel, P., 2007. Marktmacht in der Elektrizitätswirtschaft - Welche Indizien sind aussagekräftig, welche Konsequenzen adäquat? Energiewirtschaftliche Tagesfragen 4, 20–24.

Weidlich, A., Veit, D., 2008. A critical survey of agent-based wholesale electricity market models. Energy Economics 30 (4), 1728–1759.

Weigt, H., Hirschhausen, C. v., 2008. Price formation and market power in the German wholesale electricity market in 2006. Energy Policy 36 (11), 4227–4234.

Weron, R., Bierbrauer, M., Trück, S., 2004. Modeling electricity prices: jump diffusion and regime switching. Physica A 336 (1-2), 39–48.

Wissen, R., Nicolosi, M., 2007. Anmerkungen zur aktuellen Diskussion zum Merit-Order Effekt der erneuerbaren Energien. EWI Working Paper Nr 07/3.

Wuertz, D., Chalabi, Y., 2009. Package fGarch in Rmetrics – Autoregressive Conditional Heteroskedastic Modelling. http://www.rmetrics.org.

Xiong, G., Okuma, S., Fujita, H., 2004. Multi-agent Based Experiments on Uniform Price and Pay-as-Bid Electricity Auction Markets. IEEE Conference on Electric Utility Deregulation, Restructuring and Power Technologies.

Zachmann, G., 2008. Electricity Wholesale Market Prices in Europe: Convergence? Energy Economics 30 (4), 1659–1671.

Ziel, F., Steinert, R., Husmann, S., 2015. Forecasting day ahead electricity spot prices: The impact of the EXAA to other European electricity markets. Energy Economics 51, 430–444.