Simulation-based Valuation of Project Finance Investments
– Crucial Aspects of Power Plant Projects

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List of Abbreviations

APT	Arbitrage Pricing Theory
AR	Autoregressive
ARCH	Autoregressive Conditional Heteroskedasticity
ARMA	Autoregressive Moving Average
BaFin	Bundesanstalt für Finanzdienstleistungsaufsicht
BMWi	Bundesministerium für Wirtschaft und Technologie
CAPM	Capital Asset Pricing Model
CCC	Constant Conditional Correlation
CF	Cash Flow from Operations
CfD	Contract for Difference
CFTC	Commodity Futures Trading Commission
CO2	Carbon Dioxide
DCC	Dynamic Conditional Correlation
DCF	Discounted Cash Flow
DRA	Debt Repayment Amount
DSCR	Debt Service Cover Ratio
EAU	Emission Allowance Unit
EBIT	Earnings before Interest and Taxes
EBITDA	Earnings before Interest, Taxes, Depreciation, and Amortization
ECC	European Commodity Clearing
ECDP	Expected Cumulative Default Probability
EEG	Erneuerbare Energien Gesetz
EEX	European Energy Exchange

EGARCH	Exponential General Autoregressive Conditional Heteroskedasticity
EMEA	Europe, Middle East and Africa
ENTSOE	European Network of Transmission System Operators for Electricity
EnWG	Energiewirtschaftsgesetz
EU ETS	European Union Emission Trading System
EUREX	European Exchange
EXAA	Energy Exchange Austria
FCFE	Free Cash Flow to Equity
FCFF	Free Cash Flow to the Firm
FFO	Funds from Operations
FOCF	Free Operating Cash Flow
GARCH	General Autoregressive Conditional Heteroskedasticity
GDP	Gross Domestic Product
GJR-GARCH	Glosten, Jagannathan and Runkle - General Autoregressive Conditional Heteroskedasticity
GW	Gigawatt
IEA	International Energy Agency
IFRS	International Financial Reporting Standards
IGSSE	International Graduate School of Science and Engineering
IRR	Internal Rate of Return
kWh	Kilowatt Hour
KWK	Kraft-Wärme-Kopplung
LLCR	Loan Life Cover Ratio
LPX	Leipzig Power Exchange
MA	Moving Average
MATLAB	Matrix Laboratory
MW	Megawatt
MWh	Megawatt Hour

NPV	Net Present Value
NPVCR	Net Present Value Cover Ratio
NYISO	New York Independent System Operator
NYMEX	New York Mercantile Exchange
OTC	Over-the-Counter
PFVT	Project Finance Valuation Tool
PHELIX	Physical Electricity Index
PJM	Pennsylvania, New Jersey, and Maryland
PLCR	Project Life Cover Ratio
PTR	Physical Transmission Right
QMV	Quasi-Market Valuation
SPC	Special Purpose Company
SPE	Special Purpose Entity
SPV	Special Purpose Vehicle
TSO	Transmission System Operator
TUM	Technische Universität München
TWh	Terawatt Hour
WACC	Weighted Average Cost of Capital
WpHG	Wertpapierhandelsgesetz
XETRA	Exchange Electronic Trading

Chapter 1

Introduction

According to the International Energy Agency (IEA), "the capital required to meet projected energy demand through to 2030 is huge, amounting in cumulative terms to $26 trillion (in year-2008 dollars) – equal to $1.1 trillion (or 1.4% of global GDP) per year on average ...".[1] Considering also the importance to economic development of secure energy supply, ensuring sufficient capital investments in the energy sector is and will remain one of the major challenges of this century.

One of the main tasks during this process is the construction of power plants, as growth in electricity demand is projected at 76% from 2007 to 2030, translating into a required capacity addition of approximately 4,800 GW. Consequently, around 50% of the total investments are required by the power sector. These numbers can even be considered conservative estimates, based on at least two developments with highly uncertain future implications. First, 1.5 billion people worldwide currently have no access to electricity. Thus, it can be assumed that economic progress in developing countries will result in increasing investments in power plants. Second, and most important, changes in most countries' electricity policies seem necessary in order to dampen the effects of climate change. The construction of power generating facilities based on renewable energies, designed to replace fossil-fired power plants, is currently the preferred option in achieving this goal.[2]

Power plant ventures are characterized by long project lifetimes and high capital requirements, thus being highly dependent on secure economic and legal environments. However, the liberalization of the electricity markets in the 1990s transformed a

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[1] IEA (2009), p. 2.
[2] Cf. IEA (2009) for a summary of the key facts regarding the future energy policy, investments, and trends.

former stable and regulated sector into a partially competitive market, with focus shifting over the years towards price and volume uncertainty, market liquidity, and price volatility. Adjusting investment plans to these conditions poses significant difficulties to market participants. For the German electricity market, the situation is perhaps even more difficult, as the market is also subject to political interventions regarding the use of renewable energies.[3] In addition, one can assume that the prevailing uncertainty regarding the future of German nuclear power plants has been affecting long-term decisions in the electricity sector for years.

Today, a significant part of new power plants is financed via project finance, which is currently the preferred approach to financing large-scale investments.[4] The main characteristics of this financing method are risk sharing and a strong focus on the expected cash flows, due to the non-recourse character of the debt capital. These characteristics fit very well with power plant ventures, thus it can be assumed that the increased uncertainty in recent years will solidify the use of project finance in the power sector. Other potential drivers of this development include the significant energy investments needed in developing countries, where project finance is based on its legal structure often the only available financing method.

A correct valuation of a large capital investment financed via project finance depends to a significant degree on the accurate forecast of the expected cash flows. In contrast to other financing methods, where the debt capital is often collateralized, both the equity provider and the debt provider focus on this cash flow forecast. By nature, the valuation results are sensitive to the underlying assumptions; however, no consensus on the appropriate forecast technique exists, with various modeling approaches being applied in both research and real-life applications. This results in a multitude of best practice approaches and parameter specifications, but also in a lack of understanding of the crucial aspects of the valuation process. Furthermore, it is not clear whether the valuation of individual projects, such as power plant ventures, is characterized by specific aspects.

Based on these considerations, an understanding of how the valuation of a power plant venture has to take place, both from a theoretical and an implementation perspective, is of high importance. Assuming that the venture is financed via project finance, the focus must be on the cash flow modeling. A through understanding of the valuation process would permit the identification of its main drivers and also allow the evaluation of the results. Moreover, it would allow the quantification of the relationship between their robustness and modeling complexity.

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[3]Cf. section 2.2.3.3 for a discussion of these interventions.
[4]Cf. for example Esty (2004).

1.1 Aims of Analysis

The current focus of research on the topic of project finance is primarily on its qualitative aspects. Questions regarding the defining features, the determinants of its use, the legal structure, and the contractual arrangement are broadly discussed. On the other hand, the literature on project finance valuation is sparse, with only a few papers investigating the specifics valuating capital investments financed via project finance. Based on this insight, the goal of this dissertation is the development of a valuation model for project finance. As this dissertation is part of a broader research program regarding the future of energy supply, the focus of the valuation model is on power plant ventures financed via project finance.

The theoretical accuracy of the valuation process, an understanding of the crucial aspects of the valuation process, and the development of an effective, computer-based tool are intended. Three questions are of interest and need to be answered to develop such a valuation model.

The first question relates to the specifications for the development of a practicable, computer-based tool for the quantitative valuation of power plant ventures financed via project finance. I intend, together with two other doctorate students, to develop and implement a valuation tool that is based on stochastic cash flow modeling, as this is a sophisticated modeling approach of future cash flows. Stochastic modeling enables the computation of probability distributions instead of point estimates, thus resulting in more meaningful and far reaching results. In particular, this modeling approach allows the estimation of ex ante default probabilities. In addition, I intend to implement advanced forecast models for level data, volatilities, and correlations. The final result is aimed to be a self-contained, computer-based tool, which is supposed to be suitable for both equity and debt providers. The applied forecast models are selected from recent academic literature, but although stochastic cash flow modeling is a standard application in the financial literature, combining the individual forecast models with the stochastic modeling to an efficient and applicable tool is challenging. Furthermore, I intend to implement correlation structures and non-analytical distributions as an extension in order to increase the theoretical accuracy of the valuation results.

The second question relates to the choice of the electricity price time series, i.e. the market segment of the wholesale market, for the calibration of the valuation model. As the generated electricity is the only output in the case of a power plant venture, it is assumed that the electricity price is the critical profitability parameter. When examining the academic literature on electricity prices and on electricity markets, it stands out that these markets and the observed electricity prices exhibit unique

characteristics. To some extent these characteristics are due to the multitude of significant turnovers which the electricity markets have undergone over the last two decades, starting with the liberalization in the 1990s. Thus, the handling of the now exchange-traded commodity electricity is difficult. Furthermore, the characteristics of the national electricity markets differ significantly, due to different generation technologies, a lack of satisfactory transmission capacities between the single markets, and varying market structures. The focus of this dissertation is on the valuation of a power plant venture located in Germany, resulting in a focus on the German electricity market and prices. One of the unique characteristics of electricity is its non-storability, at least from an economic point of view. This results in the identification of every electricity contract as a forward contract, and thus, in a corresponding focus on the analysis of the German electricity futures market. The result of non-storability is a loose relation between the spot and the futures market; the theory of storage as the standard theory of price formation in commodity markets is not applicable in this case. Academic literature suggests that the risk premia approach is an appropriate price formation mechanism in electricity futures markets. According to this approach, electricity futures prices are built on the expected spot price at maturity of the future and of a risk premium, with empirical literature supporting this view for various markets. However, academic research on the German electricity market is just evolving. Therefore, I intend to conduct an empirical analysis of the German electricity market to contribute to this research. I aim to investigate the reliability and suitability of the risk premia approach as a theoretical price formation mechanism. I apply the ex post approach, i.e. risk premia are estimated as the price difference between futures prices and realized spot prices, and analyze all market segments that are or were in existence since the foundation of the German wholesale market.

Finally, the third question relates to the impact of model complexity on the valuation results. I define model complexity based on two dimensions, i.e. the simulation and the forecasting complexity; two dimensions that are assumed to have a significant impact on the valuation results. Simulation complexity refers to parameters of the simulation process; forecasting complexity refers to the applied forecast models. It is assumed that model complexity corresponds to valuation accuracy. However, simplifying assumptions are normally preferred as they lead to the usability of a valuation tool and an increased comprehensibility of the valuation results. I aim to quantify the impact of certain aspects; an identification of the crucial aspects is intended. Furthermore, the quantification of the impact of model complexity on the valuation results should provide information on the appropriate balance of modeling complexity and simplifying assumptions.

1.2   Structure of Analysis

This dissertation consists of a theoretical and empirical section, divided across a total of six chapters.

After the introduction in Chapter 1, the theoretical framework of the dissertation is laid out in Chapter 2. This chapter consists of three sections that cover the basics necessary as background for the empirical section.

The first section deals with project finance and the valuation of project finance investments. First, a definition of project finance and a distinction between this financing method and the traditional corporate finance is provided, followed by a discussion of the characteristics and the risks of project finance. Considerable attention is devoted to the motivation for using this financing method. A market overview is given and the key sectors in which project finance is used are pointed out. Then, the fundamentals of capital investment valuation are presented. The focus is on the discounted cash flow analysis with both the specifics of cash flow modeling and the cost of capital being addressed. Furthermore, stochastic cash flow modeling as a sophisticated modeling approach is introduced. The fundamentals of project finance valuation are addressed in the last part of the section, distinguishing between the equity and the debt provider perspective and explaining the specific requirements of these investors. The common profitability and risk measures, and their use in practice are explained, followed by an review of the quantitative literature on project finance valuation.

The second section provides an overview on the German electricity wholesale market. Starting with a description of the liberalization process of electricity markets, I discuss the establishment of electricity wholesale markets as one of the main results of this process. I subsequently report stylized facts on electricity as a commodity and on electricity prices. Afterwards, the German electricity market is addressed, with the focus on the market size, the structure of the supply and the demand side as well as the recent development of the electricity price. The end of the section provides an overview on the German wholesale electricity market, which is located on the European Energy Exchange (EEX), the German electricity exchange. Considerable attention is devoted to the market structure, the traded products, the trading process, and the market participants. This is followed by a discussion on the evolution of the observed electricity prices since the introduction of exchange trading and potential drivers of this evolution.

The last section of the theoretical framework provides an overview on price formation in commodity futures markets and, in particular, in electricity futures markets. At the beginning of the section, the theory of storage and the risk premia approach as the two standard price formation theories are discussed. Afterwards, the suitability of the

risk premia approach as a price formation mechanism in electricity futures markets is determined. In addition, the recent empirical literature is reviewed, starting with a discussion on the empirical evidence on price formation in commodity futures markets, followed by a detailed literature review on price formation in electricity markets. In this context, I distinguish between empirical evidence on short-term and long-term futures contracts.

The empirical section of the dissertation consists of three chapters. Chapter 3 introduces the newly developed stochastic project finance valuation tool while Chapter 4 contains the empirical analysis of price formation in the German electricity wholesale market. Chapter 5 addresses the impact of model complexity on the results obtained using the valuation tool.

A description of the stochastic project finance valuation tool developed in this dissertation is given in Chapter 3. The chapter begins with a discussion of the research question and introductory remarks on the valuation tool, followed by a presentation of its basic functionality, its implementation, as well as corresponding problems. Afterwards, a fundamental introduction of the valuation tool is provided, distinguishing between three basic process steps of the valuation process – input, computation, and output – in order to better illustrate the valuation process. I discuss the necessary inputs, the logic of the valuation process, and the computed results while also pointing out the status quo and present limitations of the valuation tool. The last section contains an excursus regarding time series modeling and forecasting where the forecast models implemented within the valuation tool are introduced. The chapter ends with a discussion of the obtained results and potential avenues for future research.

Chapter 4 contains the empirical analysis of the German electricity wholesale market, starting with the research question and a discussion of the analyzed data. This section also addresses the rationale behind the data selection based on a discussion of market liquidity. Then, the applied methodology and potential problems are discussed before the empirical results for the spot and futures market are reported. Furthermore, descriptive statistics on the price data are reported, followed by empirical results regarding the risk premia. The results on the magnitude and the sign of the risk premia and their potential term structure are summarized. I also present evidence relating time-variation and seasonality of the risk premia. The chapter ends with a discussion of the obtained results and potential avenues for future research.

The analysis of the impact of model complexity on the valuation results is presented in Chapter 5, which starts with a discussion of the research question and an introduction to the fundamentals of the case study. The next section illustrates the parameters and the underlying relations between them, and subsequently defines a base case parameter constellation. An understanding of the basic assumptions is

important as the focus is on the relative changes instead of the absolute results in the case study. Results relating to the impact of model complexity on the valuation results are reported in two steps. First, the impact of simulation complexity is addressed, and second, the impact of forecast complexity is examined. The chapter ends with a discussion of the obtained results and potential avenues for future research.

Chapter 6 concludes the dissertation, also addressing the implications of the obtained results and discussing concrete suggestions for further research.

Chapter 2

Theoretical Framework

The theoretical framework of this dissertation is discussed in three sections. The first section deals with the valuation of project finance, the second with the German electricity wholesale market, and the third section with price formation in commodity futures markets.

The section on the valuation of project finance, i.e. the valuation of capital investments financed via project finance, serves as an introduction to the financing method project finance, to the fundamentals on capital investment valuation, and to project finance valuation. An understanding of this financing method and its specifics is necessary for the newly developed project finance valuation tool in chapter 3 and its application on power plants financed via project finance in chapter 5.

The section on the German electricity wholesale market covers the fundamentals of the recent liberalization of electricity markets, the German electricity market, and the German electricity exchange. Moreover, the unique characteristics of the commodity electricity and of electricity prices are addressed. An understanding of these fundamentals serves as a basis for the empirical analysis of the German electricity market in chapter 4; the fundamentals are provided as the research on electricity markets is growing but these topics are not covered by standard literature so far.

The section on price formation in commodity futures markets deals with the theory and empirical evidence on price formation in these markets, in particular electricity futures markets. As the empirical analysis in chapter 4 focuses on the question whether there is evidence for the risk premia approach being an appropriate theoretical price formation mechanism in the German electricity futures market, a profound understanding of the academic literature on this topic is necessary.

2.1 The Valuation of Project Finance

Project finance has gained remarkable popularity over the past decades and today enjoys the status of the preferred financing method for large-scale investment projects. A focus on stand-alone projects, the non-recourse character of the provided debt capital, a strong dependence on an accurate estimation of the future cash flows, and an extensive risk-sharing are the main characteristics of this financing method.

In this section I introduce the financing method project finance. I begin with a definition of project finance and a discussion of its characteristics and the rationale behind its use. Moreover, I address the differences of this financing method to the traditional corporate finance. Devoting considerable attention to the involved risks, I then highlight the importance of risk management within a project finance investment, i.e. a capital investment financed via project finance. In addition, I provide an overview of today's market size and its astonishing growth over the last decades. Afterwards, I focus on the valuation of capital investment projects. I present the fundamentals with a separate discussion of the cost of capital of a company and of a project; the modeling of the expected future cash flows is addressed. A discussion of investment valuation based on cash flow modeling and its specifics is then followed by a demonstration of the benefits of the application of stochastic cash flow modeling for this purpose. Thereafter, I address the valuation of project finance investments and the different interests of the debt and the equity side. A review of the related literature regarding the valuation of project finance ends this chapter.

This section aims to answer the following three key questions:

- What is project finance and what are the characteristics, benefits, as well as risks of this popular financing method?

- What is the appropriate method to valuate capital investments and what are the specifics that have to be taken into account in the case of project finance?

- Is stochastic cash flow modeling an appropriate approach in project finance valuation and what are its advantages compared to other modeling techniques?

2.1.1   Project Finance Fundamentals

2.1.1.1   Definition of Project Finance

Finnerty (2007) defines project finance as "the raising of funds on a limited-recourse or non-recourse basis to finance an economically separable capital investment project in which the providers of the funds look primarily to the cash flow from the project as the source of funds to service their loans and provide the return of and a return on their equity invested in the project".[1] Similarly Nevitt & Fabozzi (2000) classify project finance as "a financing of a particular economic unit in which a lender is satisfied to look initially to the cash flows and earnings of that economic unit as the source of funds from which a loan will be repaid and to the assets of the economic unit as collateral for the loan".[2] Finally, Esty (2004) sees project finance as "the creation of a legally independent project company financed with equity from one or more sponsoring firms and non-recourse debt for the purpose of investing in a capital asset".[3]

There is one key element of project finance, expressed in these definitions, that is essential for this dissertation: Debt and equity providers are primarily dependent on the project's cash flow. This dependence on the expected cash flow is seen as one of the defining features of the financing method project finance in its current form.[4] While this is a common case for equity providers, debt providers often have their loans collateralized. Thus, the risk of a debt provider involved in a project finance investment is significantly higher compared to a traditional corporate finance investment.

The legal cornerstone of project finance is the creation of an independent project company, generally called a Special Purpose Vehicle[5] (SPV). The SPV is responsible for the realization of the economically separate project and it is stocked with both equity and debt. The equity is provided by equity investors, generally called sponsors, and the debt mostly by a syndicate of financial institutions.[6] After the completion of the project the SPV is usually dissolved. The SPV is created by the sponsors who initiate the project and also negotiate the debt contracts with the bank syndicate. The projects that are financed via project finance are mostly independent, i.e. stand-

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[1] Finnerty (2007), p. 1.

[2] Nevitt & Fabozzi (2000), p. 1.

[3] Esty (2004), p. 213.

[4] The definition of project finance in its current form goes back to the Financial Accounting Standard No. 47 from 1981; cf. Tytko (2003), p. 13.

[5] Alternative terms for SPV are Special Purpose Entity (SPE) or Special Purpose Company (SPC).

[6] Cf. for example Simons (1993), Dennis & Mullineaux (2000), Pichler & Wilhelm (2001), and Sufi (2007) for a discussion of the rationales of bank syndicates.

Figure 2.1
Loan-based Financing of Projects versus Project Finance
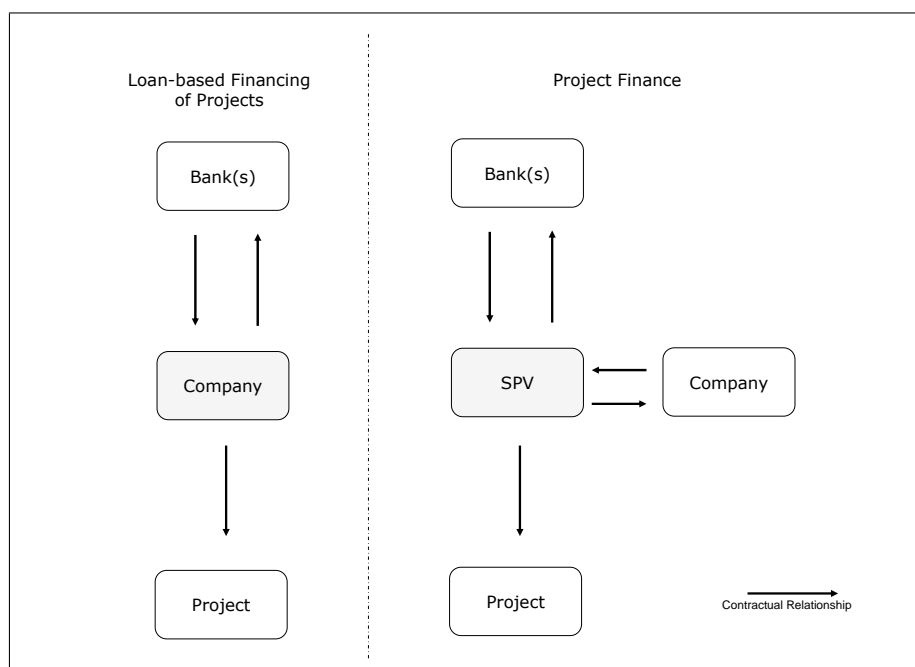
Source: Own work.

alone projects. Furthermore, the projects are often very specific, characterized by low redeployability[7] and a limited economic lifetime.

The creation of an independent company, in the form of the SPV, allows the sponsors to limit their equity involvement to the initial capital amount. The SPV is the sole borrower and all rights and responsibilities within the project are taken by this entity. In the case of a project default, the SPV is the only entity filing for bankruptcy. Thus, the sponsors primarily have the obligation to contribute their equity stake. Normally, there is no collateralization of the debt capital on the part of the sponsors and the debt is non-recourse.[8]

In the following it is important to distinguish between the terms project finance and project financing. In this dissertation, project financing will be used as a general term relating to the financing of a project without specifying how the project is financed; project finance, on the other side, will be used for the specific financing method that is defined above.

Figure 2.1 illustrates the general structure of a project finance investment versus a

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[7]Cf. Habib & Johnsen (1999), pp. 707-708.

[8]However, contractual agreements with collateralization features also exist; these contracts are known as limited recourse.

traditional corporate finance, i.e. a loan-based financing of a project.[9] The main difference between the loan-based financing and the project finance is that, in the first case, the company acts as borrower and the debt capital is secured with its whole balance sheet.[10] If the project fails, the company may be forced into bankruptcy if it is not able to repay the debt. In the case of a project finance investment, only the SPV has legal obligations towards the bank(s). The maximum amount the sponsors stand to lose is capped at the level of its total equity stake. This difference in liability has significant implications regarding the granting of debt capital, which will be discussed in section 2.1.3.2.

2.1.1.2   Characteristics of Project Finance

The following characteristics are, in general, attributed to the financing method project finance:

1. Cash flow-related lending,

2. Non-recourse lending,

3. Off-balance-sheet financing,

4. Risk-sharing, and

5. High leverage.

The first characteristic – project finance as a cash flow-related lending method – is based on the legal structure of project finance. Since the SPV acts as the sole borrower – and because the SPV is, in general, exclusively founded for the financing of the project – only two sources of collateral are available. The first source is the assets acquired within the project; the second source is the expected cash flow. In general, the acquired assets are very specific; low market values and liquidation proceeds are the consequence.[11] Thus, from a debt provider's point of view, the success of a project finance investment is almost solely dependent on the profitability of the specific project, i.e. the ex ante unknown and uncertain cash flows.[12]

The second characteristic of project finance is that the provided debt capital is normally non-recourse. This is due to the legal status of the SPV as a stand-alone

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[9]Cf. Ghersi & Sabal (2006) for a schematic comparison of corporate finance and project finance.

[10]Cf. section 2.1.3.1 for a discussion of the traditional loan process.

[11]Project finance is mainly used for large-scale investments; the capital assets acquired within these transactions often have very specific designs and dimension and they are often not even transportable.

[12]Kleimeier & Megginson (2001) state that "project finance is used primarily to fund tangible-asset-rich and capital intensive projects with relatively transparent (often hard-currency) cash flows"; Kleimeier & Megginson (2001), p. 8.

entity. Non-recourse refers to the fact that the debt providers have no rights in regards to the sponsors' assets in case the project fails. This legal situation leads to the debt providers taking on parts of the business risk[13]. In order to partially migrate this risk, debt providers have to estimate the expected cash flows of the project over its entire lifetime as accurately as possible.[14]

The third characteristic – project finance as an off-balance-sheet financing – is also closely related to the foundation of the SPV as a legally independent entity. According to the International Financial Reporting Standards (IFRS), shares below 50% in a SPV are to be recognized on the investor's balance sheet using the equity method.[15] Thus, it is only the equity stake, and not the whole balance sheet of the SPV, that is activated when the share is below this threshold. In this case, the sponsor avoids the decline of the equity ratio, due to the SPV's often very high debt-to-equity ratio as discussed below. Normally, a project finance investment is initiated by one to three sponsors. However, in general, one majority shareholder controls the project.[16] Thus, the characteristic off-balance-sheet financing is not a defining feature of project finance since it only holds for the minority sponsors.

Another common characteristic of project finance is risk-sharing. As will be more fully discussed in section 2.1.1.4, in general, there are dozens of parties involved in a typical project finance transaction. The rationale is that the involved parties try to optimally allocate the individual risks to the parties that are able to bear them. Therefore, packaging and transferring of risks is one of the main characteristics of this financing method.[17] Due to the resulting involvement of a high number of parties and, hence, the high number of contracts that have to be negotiated Esty (2004) remarks that "..., some people refer to project finance as 'contract finance' ".[18]

High leverage is another characteristic of project finance that is often discussed in the corresponding literature. The high debt-to-equity ratios in project finance are the direct result of the risk-sharing. An effective financing structure can be reached through efficient risk-sharing, resulting in the ability to achieve a high ratio of debt capital. Capital structures with high debt ratios are frequently observed; the average SPV has a debt-to-capital ratio of 70%, compared to an average ratio of 33% for

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[13]Cf. Kleimeier & Megginson (2001), p. 3.

[14]Financial modeling, i.e. the application of advanced mathematical modeling techniques in the context of finance, plays a more and more critical role in the context of project finance.

[15]When applying the equity method to account for the investment in an associated company the initial investment is activated at cost. Thereafter, the book value is increased or decreased to recognize the investor's share of the profits or losses; cash distributions received after the acquisition decrease the book value. Cf. for example Penman (2007) for a further discussion.

[16]Cf. Esty & Sesia (2010), p. 10. The authors also report that in 60% of all project finance transactions only one sponsor is found on the equity side.

[17]Cf. Marti & Keith (2000), p.2.

[18]Esty (2004), p. 216.

public companies.[19] The debt is generally provided by a bank syndicate. It is characterized by larger absolute amounts and longer maturities versus other syndicated loans.[20]

2.1.1.3 Motivation for the Use of Project Finance

When Airbus Industries decided to develop the A380 total project costs were estimated at 13 billion U.S. Dollar. For a company with yearly total sales of 17 billion U.S. Dollar this represents a capital amount that could obviously lead into bankruptcy in the case of project failure. Therefore, the investment may be seen, as stated by Esty (2004), as a kind of bet-the-company investment.[21] It is thus not realistic to characterize the corporate manager facing this decision as the rational 'accept every positive net present value (NPV) project' decider. It rather seems traceable that the management of a company might reject a positive NPV investment due to concerns on the dimension and the risks. The fear is dragging the company into bankruptcy in the case of project failure. Based on these considerations the academic literature postulates that the size of an investment project affects a manager's willingness to bear risk.[22]

Using project finance to finance large-scale projects has the advantage that the sponsor's maximal loss is generally capped at its initial investment in the project. Thus, managers might be willing to take more risk when using this financing method. Financing of large-scale projects via project finance could have the aggregate result that more profitable investments are conducted. Underinvestment due to managerial risk aversion would also be reduced.[23]

Academic literature also suggests that project finance can reduce underinvestment due to asymmetric information as introduced by Myers & Maljuf (1984) in their famous work on the determinants of capital structures. Furthermore, underinvestment due to debt overhang could be reduced.[24]

In addition, the structure of project finance can diminish agency conflicts as introduced by Jensen & Meckling (1976). According to Jensen's Free Cash Flow Hypothesis (Jensen (1986)) high debt-to-equity ratios serve as an important disciplinary instrument: They prevent managers from wasting or mis-allocating free cash flows

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[19]Cf. Esty (2003), p. 7.

[20]Esty & Megginson (2001) analyze project finance loan tranches. Using a sample of 495 project finance loan tranches (with an overall worth of 151 billion U.S. Dollar) the authors find that the largest single bank has on average a share of 20.3% on a single tranche and that the top five banks hold 61.2% of a tranche.

[21]Cf. Esty (2004), p. 220.

[22]Cf. Esty (2004), p. 220.

[23]Cf. Esty (2004), p. 217.

[24]Cf. Esty (2003), p. 22.

to inefficient investments. Thus, the use of project finance reduces incentive conflicts between the capital providers; agency costs are reduced and the expected free cash flows increase as a result.[25]

Summarizing the arguments above project finance is another example for the inadequacy of the famous Proposition I – capital structure, respectively financing decisions, do not matter in perfect markets – of Modigliani & Miller (1958) when considering real, i.e. imperfect, markets. The financing of capital investments via project finance can have the effect that sponsors undertake more risky projects than they would be willing otherwise.[26] Regarding capital investment in developing countries and emerging markets, for example, project finance plays a significant role. It is often the only financing method available, in particular for large-scale projects. This is due to the high risk of projects in these countries and markets; risks that a solid project finance structure may face efficiently. Academic literature suggests that the use of project finance in these countries serves as an important driver for economic growth[27] and helps filling the infrastructure gap.[28]

However, several drawbacks have to be mentioned, even though the popularity of project finance seems to prove that market participants are willing to accept them. One drawback is the additional time that it takes to create the SPV, taking from 6 up to 18 months longer compared to alternative financing methods. Another disadvantage is represented by high transaction costs, reaching often 5-10% of the project's total costs.[29] Also the up-front fees (plus advisory fees relating to the structure of the project finance transaction) and interest rates are considerably higher than for corporate finance transactions.[30]

2.1.1.4 Project Finance Risks

Project finance is exposed – similar to other financing methods – to a multitude of risks. Before I discuss the individual risk, I first classify these risks in accordance with the broad literature in four categories, namely technical, environmental, economic, and political[31] risks. Figure 2.2 contains a summary of the potential risks, classified in the four categories, arising in a typical project finance investment.[32]

Technical risks associated with the construction of the project are at the main concern

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[25]Cf. Subramanian et al. (2007) for a theoretical model that allows to derive this result.

[26]Cf. Culp & Forrester (2010), p. 2.

[27]Cf. Kleimeier & Versteeg (2009), p. 3.

[28]Cf. Hammami et al. (2006), p. 5.

[29]Cf. Esty (2004), p. 216.

[30]Cf. Subramanian et al. (2007), p. 1.

[31]Cf. Hainz & Kleimeier (2006) for a discussion of the political risks in project finance.

[32]Cf. also Decker (2008), pp. 145-148 and Przybilla (2008), pp. 93-100 for a compilation of potential risks in project finance investments.

Figure 2.2
Project Finance Risks

Technical risks	Environmental risks
• Completion risk • Latent defects risk • Risk of breakdown • (Technical) underperformance …	• Risks caused by environmental effects on / of a project • Force majeure risk (e.g earthquakes, floods, …) • Accidents …
Economic risks	Political risks
• Commodity price risk • Cost overrun risk • Operational risk • Currency risk • Market risk (Introduction of substitutes; better technology, …) …	• Expropriation risk • Currency convertibility risk • Transferability risk • Political violence risk (war, sabotage, terrorism) • Regulatory risk …

Source: Own work.

during the early stage of a project. In addition, the project is in particular exposed to environmental risks in this stage. During the operational phase the main risks associated with the underperformance or even failure of the project due to economical or political circumstances become of main importance.[33]

Completion risk is the main technical risk. This risk includes the possibility that the project might not be completed, often implying a total loss for both the equity and debt providers. The failed completion of a project can be either cost- or technology-related. Another technical risk is technical underperformance, meaning that a project is completed but never reaches the projected output and hence not the expected level of cash flows.

Environmental risks can be divided into two risk categories; generally they are present for the whole lifetime of the project but of particular importance at the beginning of the project. The first category reflects the effects of the project (construction) on the environment (e.g. air pollution, ground water pollution, ...). These effects can cause high costs and even force the sponsors to redesign the project. The second risk category is related to the force majeure risks (e.g. fires, earthquakes, ...) and other not directly avoidable catastrophes that can seriously damage or even

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[33]Cf. Sorge (2004), p. 94.

completely destroy the project.

Following the technological project completion economic risk becomes the main concern. Examples of economic risk are commodity price risk, i.e. higher input costs than expected, and demand risk, i.e. the failure to reach the projected output levels due to lower demand. Finally, political risks include risks such as the host government changing the regulatory environment or devaluing the currency. Political risks also include the risk of expropriation.

2.1.1.5 Project Finance and Risk Management

Addressing the risks discussed above, i.e. an effective risk management, plays a distinct role in project finance. Although this is also for other financing methods relevant, risk management is of special importance in project finance. This is due to the fact that the expected cash flows represent the majority of collateral to the debt providers. Thus, debt providers have a strong incentive to hedge as many risks as possible in order to secure predictable cash flows. The aim of hedging is the reduction of future cash flow variability and probability of default. It also reduces potential difficulties of the SPV in meeting its regular interest and loan repayments and thus the probability of a necessary restructuring. The existing risk factors need to be hedged to an extent where future cash flows become predictable to acceptable levels for the debt provider.

The debt providers' requirement to hedge as many risk as possible confronts the sponsors with the situation that the degree of risk management of a project not only directly impacts the cost of debt but effectively also the accessibility to debt capital. A certain minimum degree of hedging is expected by the market and has to be provided. Thus, the sponsors do not face the question whether or not to hedge but only to which extent. The corresponding literature indicates that as a consequence hedging (at least through the non-financial contracts discussed below) takes place before the negotiation of the debt contracts. This hedging activities of the sponsors are even more amplified by the fact that the debt providers, almost exclusively banks, have a favorable negotiating position since bank loans are the primary source of debt capital in project finance.[34]

The possibilities to hedge the arising risks include mainly the use of insurance, of financial contracts, and of non-financial contracts. Another possibility is the use of third party guarantees which are particularly used in respect to certain political risk.[35]

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[34]Cf. Beale et al. (2002), p. 6.
[35]Cf. Sorge & Gadanecz (2008), p. 68.

Insurance is primarily used to hedge force majeure risks, e.g. fire, water damage or terrorist attacks. Insuring force majeure risks is usually mandatory in project finance investments. Also common is the insurance of political risks through export credit agencies.[36]

Financial contracts are often used in project finance transactions for hedging short-term risks. Examples include future contracts which are used to hedge the input and output factor prices, not secured by long-term contracts. However, the vast majority of financial contracts are used for hedging market-wide risks, i.e. macroeconomic risks as foreign exchange risk, interest rate risk and inflation risk.

Non-financial contracts are the main hedging instrument used in project finance. The sponsors usually sign a multitude of contracts to reduce the project's risks, i.e. to shift the risks from the SPV to third parties willing to bear them.[37] The result is a wide network of contracts, such as long-term agreements on the input and output factors, precisely defined construction contracts and detailed operating and maintenance contracts. Construction contracts, for example, are generally designed in a manner that the responsible construction company is obligated to compensate the SPV for delays and for other failures.[38] In particular, it is important to hedge the input and output factor price risk.[39] Due to the popularity of project finance in the energy and mining sector commodity price risk is widely seen as the main risk in a project finance investment.[40]

Regarding the non-financial contracts Corielli et al. (2008) identify four types of contracts that are critical for the soundness of a project finance investment:[41]

1. Construction contracts,

2. Purchasing agreements,

3. Selling agreements, and

4. Operation and maintenance agreements.

Construction contracts include all contracts concerning the completion of the project. Purchasing and selling agreements include all contracts that intend to secure the

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[36]Cf. Klompjan & Wouters (2002), p. 2.

[37]Cf. Lessard & Miller (2001), pp. 12-14.

[38]Another possibility to hedge the completion risk from the point of view of the debt providers is to ask for a sponsors' guarantee for delay risk. This kind of bilateral agreement is also used for other specific risks where the debt providers secure their positions through contracts with the sponsor.

[39]Take-or-Pay contracts and Put-or-Pay contracts are examples for hedging instruments regarding the input and output factor risks; cf. Tytko (2003), p. 32.

[40]Cf. Spillers (1999), p. 1.

[41]Cf. Corielli et al. (2008), pp. 9-10.

input and the output prices. Operating and maintenance agreements are contracts that aim to secure the current costs.

Summarizing, project finance is characterized through a network of (non-financial) contracts.[42] The advantage of these contracts is that they can be used to address risks that are project-specific and that cannot be hedged in financial markets.[43] The aim is to reduce the cash flow variability and to avoid the negative impact of unexpected events causing a decrease of the cash flows. Esty (2003) estimates that a typical project finance transaction involves around 15 different parties and 40 or more contracts. Larger deals can involve significantly higher numbers of parties and contracts.[44] Gatti et al. (2008) find that debt providers seem to rely on the various contracts not just as a mechanism for controlling project risks but also agency costs, an additional motivation for the use of project finance discussed in the section above.

Another risk reduction mechanism often found in project finance investments is the use of covenants.[45] As a consequence of the interest divergence between sponsors and debt providers project finance is characterized by an intense use of covenants[46] in the debt capital contracts.[47] The debt providers are using covenants to align the sponsors' interest with their own, i.e. to improve the monitoring quality and to reduce managerial discretion.[48]

The creation of reserve accounts is another risk reducing instrument used by debt providers. A reserve account is created for the case that the cash flows of one or more consecutive periods are not sufficient to serve the mandatory debt payments. To avoid project failure due to a few periods with cash flows lower than assumed, the sponsors usually agree not to withdraw dividends until a certain amount has been deposited in specific reserve accounts.

Figure 2.3 shows a typical project finance structure as found in the energy industry.[49] The project is a gas-fired power plant. The project is financed by two sponsors on the equity side and a bank syndicate on the debt side. In this example the contractual structure consists of a supply contract for the gas input and a purchase contract for the power output. In reality these contracts often have long maturities, sometimes

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[42]Cf. Dailami & Hauswald (2001) for a discussion of project finance as a nexus of contracts.

[43]Cf. Dailami et al. (1999), p. 2.

[44]Cf. Esty (2003), p. 8.

[45]Cf. Fahrholz (1998), pp. 276-278.

[46]Covenants are legal clauses included in loan contracts. They specify one or more conditions that have to be obligated by the borrowing party. In the case of a breach of the covenants the lender often has the possibility to call the loan within a short term.

[47]However, parts of the empirical literature find that project finance is characterized by a lower number of covenants than in corporate finance; cf. for example Kleimeier & Megginson (2001).

[48]Cf. for example Rajan & Winton (1995) or Röver (2003) for a discussion of the motivation for implementing covenants in debt contracts.

[49]However, the illustration is strongly simplified. For the discussion of a more realistic project cf. for example Bonetti et al. (2010).

Figure 2.3
A Typical Project Finance Structure
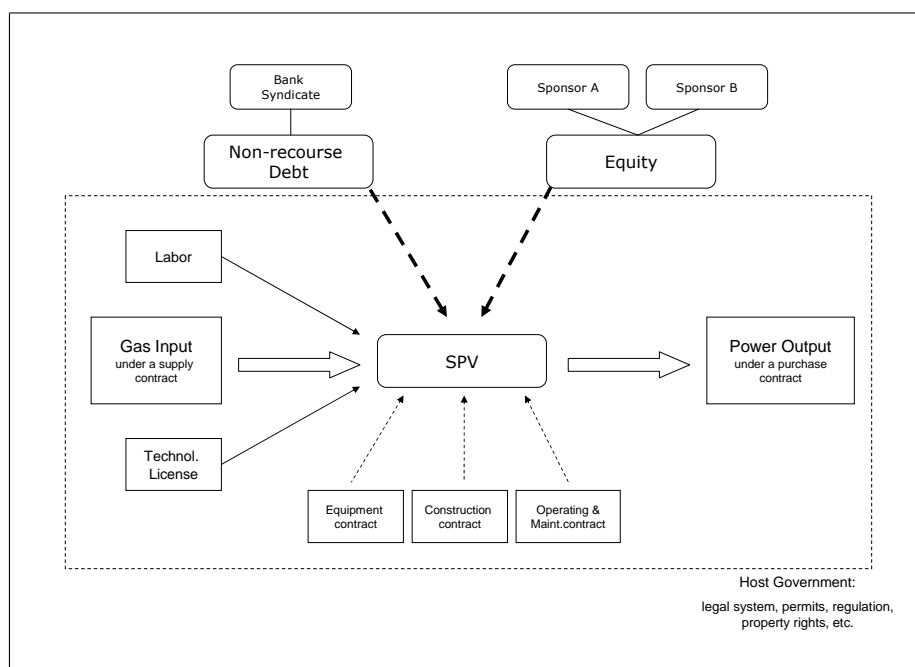
Source: Modified, taken from Esty (2003), p. 36.

decades.[50] In addition, a construction and equipment contract secures the initial capital investment. Labor contracts and operating and maintenance contracts secure the current costs. The legal environment necessary for the safe operation of the power plant is provided by the host government.

2.1.1.6 Project Finance Market

The financing of a gas and oil project in the 1930s by a Dallas bank is seen by some authors as the birth of the financing method project finance as it is known today.[51] However, financing structures with similar characteristics can be traced back to approximately 700 years ago.[52]

The exploration of the North Sea oil fields in the 1970s marks the first use of project finance on a larger scale.[53] The financial success of this project established project fi-

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[50]The ability to hedge a project's output is of course dependent on the sector in which the project finance is conducted. Long-term hedging is common in the oil, gas, and power sector. However, it is not possible in the transportation or hotel sector.

[51]Cf. for example Culp & Forrester (2010), p. 2.

[52]Cf. for example Finnerty (2007), p. 4; cf. also Esty & Sesia (2010) for an overview of the history of project finance.

[53]Cf. Kleimeier & Megginson (2001), p. 3.

Figure 2.4
Global Project Finance Loans Volume 2003-2009
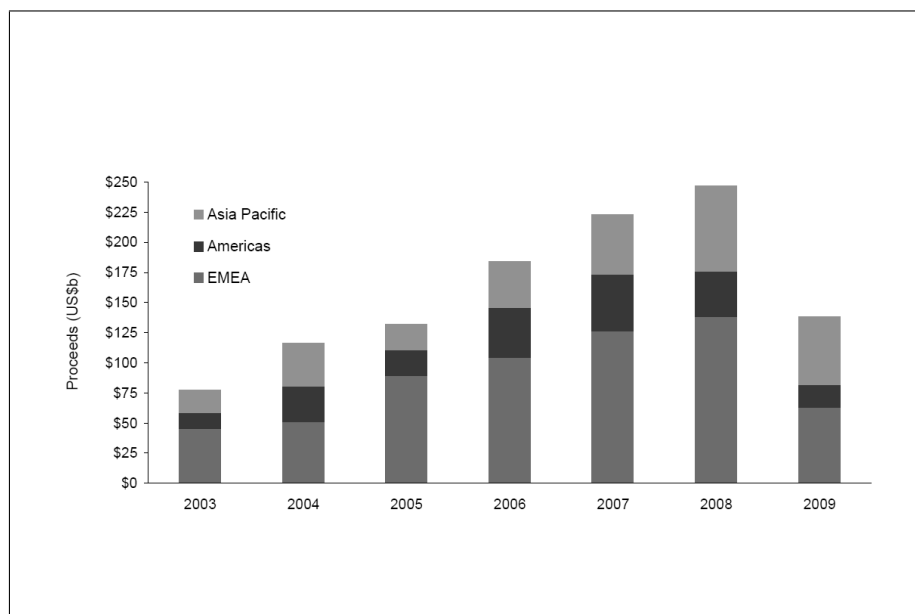
Source: Taken from Thomson Reuters (2009), p. 1.

nance worldwide as the preferred financing method for large-scale investments. Esty (2004) reports that today approximately 10 to 15% of capital investments are financed via project finance in the United States. For investments with a volume exceeding 500 million U.S. Dollar this ratio even reaches 50%.[54]

The worldwide volume of project finance has risen considerably over the last decades, from less than 10 billion U.S. Dollar annually in the late 1980s to approximately 328 billion U.S. Dollar annually in 2006.[55] During the 1990s the compound annual growth rate has been almost 20%.[56] Corielli et al. (2008) report that the compound annual growth rates for project finance loans and project finance bonds between 1994 and 2006 were recorded at 23% and 15%, respectively.[57] After an all time high of 408 billion U.S. Dollar in 2008 the market volume declined to 240 billion U.S. Dollar in 2009.[58] This decline of over 40% reflects the worldwide financial and later economic crisis.[59] In the sections above it was indicated that the risks of a debt provider in project finance are by far higher than in a corporate finance and in other financing

[54]Cf. Esty (2004), p. 214.
[55]Cf. Esty & Sesia (2007), p. 1.
[56]Cf. Esty (2004), p. 213.
[57]Cf. Corielli et al. (2008), p. 3.
[58]Cf. Esty & Sesia (2010), p. 1.
[59]In 2002, the last worldwide economic crisis, an estimated 40% decline in the project finance market was observed; cf. Esty (2003), p. 1.

Figure 2.5
Global Project Finance Loans Volume by Sector in 2009
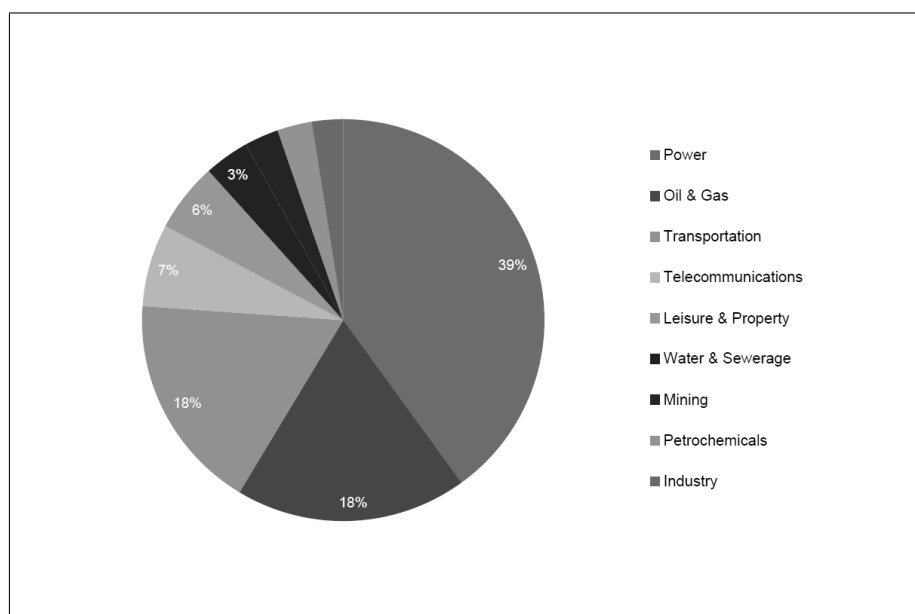
Source: Taken from Thomson Reuters (2009), p. 1.

methods. As banks tend to cut risky investments and loans in the first round of a crisis, project finance loans were the first to be cancelled after the eruption of the current crisis in 2008.

According to Hainz & Kleimeier (2004) a total amount of 963 billion U.S. Dollar has been raised between 1980 and 2003 for project finance loans.[60] Figure 2.4 shows the development of the global project finance loans volume over the last seven years. The total loan volume is broken down in the three regions Asia Pacific, Americas, and Europe, Middle East and Africa (EMEA). Apparently the strong growth from the 1990s continued into the new millennium with the market peaking in 2008.

Regarding the use of project finance by industries most applications are found in the infrastructure sector (e.g. toll roads), energy sector (e.g. power plants), and natural resource sector (e.g. mines).[61] Figure 2.5 breaks down the 2009 project finance loans volume across the sectors, showing that almost 40% of the whole market consists of power projects. Oil and gas (18%) and Transportation (18%) are the other two significant sectors in the market.

The most prominent examples of project financed investments in recent years include the four billion U.S. Dollar Chad-Cameroon pipeline, the six billion U.S. Dollar

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[60]Cf. Hainz & Kleimeier (2004), p. 2.
[61]Cf. Esty (2004), p. 214.

Irdium global satellite telecommunications system, the 18 billion U.S. Dollar Papua New Guinea Liquified Natural Gas project and the 29 billion U.S. Dollar Sakhalin II gas field.[62]

Looking back to the 1990s, the construction of the Disneyland Europe and of the Eurotunnel between France and the United Kingdom are probably the most prominent projects financed by project finance. In particular the Eurotunnel is an interesting case study as it was the largest capital investment ever to be financed via project finance. It ended in a financial disaster from which many lessons can be learned.[63] The significant cost underestimation observed during the Eurotunnel construction is also characteristic for many other projects.[64]

2.1.2 Capital Investment Valuation

2.1.2.1 Fundamentals

The term valuation, in general, refers to the determination of the economic value of an asset, liability or capital investment.[65] The valuation process is mostly based on an approach such as the discounted cash flow (DCF) analysis or relative valuation methods such as the multiples method.

In the following, I focus on the valuation in the context of capital budgeting, i.e. the valuation of capital investments.[66]

The valuation of capital investments is focused on the question whether investing in a certain project makes economic sense. The DCF analysis is, at least when large capital investments (under certainty) are valuated, the most common concept applied today.[67] However, other methods as the internal rate of return (IRR) or the payback period are used as well.[68]

The DCF analysis is based on the calculation of the present value of the future cash flows, i.e. the future cash flows are estimated and discounted. The sum of all discounted cash flows, both incoming and outgoing, is the NPV.[69] The basic decision

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[62]Cf. Esty & Sesia (2010), p. 1.

[63]Cf. Vilanova (2006) for a discussion of the Eurotunnel venture.

[64]Cf. Flyvbjerg et al. (2002) for an analysis of the phenomenon cost underestimation in transportation projects.

[65]I always use the term *value* as market value in this dissertation.

[66]The theory for the valuation of investment projects has significantly improved over the last century. Taking the equity provider's point of view, the payback method has been the most common concept for determining profitability at the beginning of the last century. Nowadays, the DCF analysis is the most common concept. Recent literature has already begun discussing whether the real options approach is more suitable to value investment projects, at least in certain industries.

[67]Cf. Graham & Harvey (2001) for a survey on the valuation methods used in practice.

[68]Cf. for example Ross et al. (2005) for a discussion of alternative investment rules.

[69]Cf. Fernandez (2009) for a discussion of the various valuation methods based on cash flows.

rule underlying the NPV method is going forward with projects that have a positive NPV and rejecting projects with a negative NPV.[70]

Primarily, the DCF analysis is used to value equity investments in two ways: First, indirectly by discounting the free cash flow to the firm (FCFF)[71] with the help of the cost of capital[72] and subtracting the debt value (adjusted by cash reserves) afterwards. Second, by directly discounting the free cash flow to equity (FCFE)[73] using the cost of equity.

In the first case, the result of the FCFF approach is the entity value defined as

$$NPV_{Entity\ Value} = \sum_{t=1}^{n} \frac{FCFF_t}{(1 + r_c)^n} \tag{2.1}$$

with $FCFF_t$ the free cash flow to the firm in period t, r_c the cost of capital (assumed to be constant) and n the lifetime of the investment (project, enterprise, etc.).

In the second case, based on the same assumptions as above, the result of the FCFE approach is the equity value

$$NPV_{Equity\ Value} = \sum_{t=1}^{n} \frac{FCFE_t}{(1 + r_e)^n}. \tag{2.2}$$

Instead of the free cash flow to the firm the FCFE is used. In addition, the cost of capital is replaced by the cost of equity, r_e.

The equity value reflects the value of an investment to the equity providers; the entity value reflects the total value of the investment to all capital providers. In reality, the FCFF approach is more common because, as stated by Copeland et al. (2000), "discounting equity cash flows provides less information about the sources of value creation and is not as useful for identifying value-creation opportunities".[74]

Two types of issues arise at this point: First, the determination of the risk-adjusted cost of capital (equity) is not straightforward. Second, it is of significant importance to account for the uncertainty of the future cash flows.

The appropriate method to determine the cost of capital is discussed in the next section, whereby the determination of the cost of equity is the crucial task in real-life applications. Regarding the uncertainty of the future cash flows Vose (2000) points

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[70]Cf. for example Ross et al. (2005), Copeland et al. (2005), and Brealey et al. (2007) for a discussion of the NPV method.

[71]The FCFF is the amount of generated cash that can be – after deduction of the necessary reinvestments – distributed to both the debt and the equity providers.

[72]Cf. the next section for a definition of the cost of capital for a company.

[73]The FCFE is defined as the FCFF minus debt repayments and changes in the net debt capital.

[74]Copeland et al. (2000), p. 151.

out that the main solutions that allow for the consideration of the future uncertainty in capital investments are either a deterministic scenario-based modeling approach or the application of stochastic modeling. Both methods are discussed in the following including their advantages and their drawbacks.

2.1.2.2 Cost of Capital

The cost of capital of a company is the average cost of a company's funds.[75] The funds of a company normally consist of a mix of equity and debt capital. In addition, capital categorized in between these two fundamental capital sources exists in reality as well.[76] The weighted average cost of capital (WACC) is, in general, used as a measure of the average capital cost.[77] The cost of capital of a company is the expected return of a hypothetical investor allocating capital in a portfolio of all the company's existing securities.[78] In reality, the WACC is mostly calculated as a weighted average of the cost of equity, i.e. the expected return on the current equity capital, and the cost of debt, i.e. the expected return on the current debt capital.

In the case of an capital investment the cost of capital is the minimum rate of return that an investor expects from his investment. The same return can be earned by investing in an alternative project with equivalent risk (opportunity costs). Hurdle rate is another term used in this context.

Cost of equity

The cost of equity is usually estimated with the Capital Asset Pricing Model (CAPM), extensions of the CAPM or with the Arbitrage Pricing Theory (APT).[79] The CAPM is by far the most often used approach in real-life applications.[80]

The CAPM states that the cost of equity is equal to the sum of the risk-free rate and the equity risk premium times a factor related to the systematic risk, called beta in the financial literature.[81] Two points relating to the estimation of the systematic

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[75]Cf. Copeland et al. (2005) for a discussion of the cost of capital and their determination or, rather, estimation.

[76]Funds categorized between equity and debt are usually called mezzanine capital.

[77]The WACC is defined as

$$WACC = \frac{Equity}{Equity + Debt}r_e + (1 - T)\frac{Debt}{Equity + Debt}r_d$$

where r_e are the cost of equity and r_D the cost of debt. T is the tax rate and *Equity* and *Debt* the market values of the equity and debt capital, respectively.

[78]Cf. Brealey et al. (2007), p. 215

[79]The CAPM was developed by Sharpe (1964), Lintner (1965), and Mossin (1966). The APT was developed by Ross (1976). Both models build on the work of Markowitz (1952) on diversification and portfolio theory.

[80]Cf. Graham & Harvey (2001), p. 201.

[81]Cf. Fama & French (2004) for a discussion of the theory and empirical evidence regarding the

risk are of interest for this dissertation: First, what is the right beta to valuate a capital investment and second, is this beta stable over the lifetime of the project or is it rather time-dependent.

An application of the CAPM for the estimation of a company's beta results in an estimate of the cost of equity of the company. However, this cost of equity can only be used for the valuation of a capital investment when the risk of the investment is equal to the average risk of the company. In addition, the investment needs to be financed with the same capital mix as the actual mix of the company. Otherwise, an appropriate levered beta must be used.[82] In the case that the risk of the investment is not equal to the company's risk a specific cost of equity for the investment must be determined.[83]

Regarding the time-dependence of the beta, the DCF analysis in classical valuation theory is mainly applied to industry companies with rather stable capital structures. Therefore, a single, constant discount rate can be used. However, this procedure is not appropriate for the valuation of capital investments financed via project finance since they are characterized by limited lifetimes and time-varying capital structures. One solution recommended by the academic literature is the assumption of a target capital structure which allows the calculation of a discount rate.[84] This approach may lead to a miscalculation of the project's cost of equity since the costs of equity depend on the project's capital structure.[85] Damodaran (1994) and Grinblatt & Titman (2001) argue that only the application of different discount rates for every period based on the actual capital structure produces an unbiased cost of equity.[86]

Esty (1999) argues that it is crucial to calculate the cost of equity based on market values of debt and equity instead of their book values. However, this leads to a circularity problem: The market value of equity, which is calculated as the sum of the book value of equity and the NPV, cannot be calculated since the cost of equity is necessary for that. A possible solution, first applied to project finance valuation by Esty (1999), is the so called quasi-market valuation (QMV).[87] According to this method the market value of equity at the end of the first year equals the initial book value of equity plus the expected NPV of the project.

CAPM.

[82]Cf. Kaplan & Ruback (1995), pp. 1064-1068.

[83]Cf. Brigham et al. (1999), pp. 168-175.

[84]Cf. for example Ehrhardt (1994) and Finnerty (2007).

[85]Cf. Esty (1999) for a discussion of this problem. This mis-estimation of the cost of equity also distorts the calculation of the WACC.

[86]I use this procedure in the newly developed project finance valuation tool by determining the cost of equity each time the cash flow is calculated. Cf. chapter 3 for a discussion of the exact calculation procedure.

[87]The QMV is based on three assumptions, namely that (i) the CAPM is valid, (ii) the market value of debt is equal to the book value, and (iii) the market is efficient.

Due to the advantages of the QMV method, it is implemented and used in the newly developed project finance valuation tool which is introduced in chapter 3.[88]

Cost of debt

The calculation or rather estimation of the cost of debt is mostly straightforward. Common methods to determine the cost of debt are, for example, the risk premium approach, i.e. the cost of debt are estimated as the sum of the risk-free rate and an appropriate risk premium, or the benchmarking with comparable debt securities. I do not discuss the individual approaches separately here and refer to the standard financial literature. However, I note that it is important to distinguish whether the cost of debt is reported before or after tax. Normally, they are reported before tax but since the actual cost of debt is reduced by the level of the company's tax benefit the effective cost is equal to the cost of debt after tax.

In the case study in chapter 5, the cost of capital is seen as a constant input factor which is specified at the beginning of the valuation process and remains unchanged thereafter.

2.1.2.3 Cash Flows

A cash flow, to use a simple and fundamental definition, is the difference between the cash that moves in and out of a certain entity during a certain period. In contrast to profits that are based on accounting principles, cash flows are based on the observable movements of cash. To determine cash flows both the direct and the indirect method can be used. The direct method sums up observed cash outflows and inflows, the indirect method starts with an accounting measure, normally the net income, and corrects it with all non-cash charges.[89]

One of the main advantages of the use of cash flows is its role as an alternate measure of profits. It is widely believed that accrual accounting concepts, due to the wide choice of parameters, do not represent economic realities, at least in the short-term. In other words, insiders can use various parameters of choice to manipulate financial results in their favor. Besides, it is assumed that it is more difficult to manipulate cash flows than profits. Thus, almost all modern valuation methods are based on cash flow measures and not on accounting profits.

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[88]Cf. chapter 3 for a discussion of the implementation of the QMV method within the developed project finance valuation tool.

[89]Three sources of cash flows are usually distinguished in the financial literature and financial reports: Cash flows from (i) operating activities, (ii) investment activities, and (iii) financing activities. Operating cash flows are generated from activities related to selling products, investing cash flows by purchasing assets, and financing cash flows result from cash transactions with claimants. Cf. for example Penman (2007) for a further discussion.

2.1.2.4 Cash Flow Modeling

Cash flow modeling is an integral part of the capital budgeting process. The aim is to find a methodology that is suitable to forecast future cash flows and to use this method in such a way that the obtained results are meaningful.[90]

The most common approach used in cash flow modeling is the fundamental analysis. Fundamental analysis relies on historical data, e.g. financial reports and historical time series, and aims to derive future values based on these data. In a simple forecast model values from the current financial statement are used to predict future values. A simple extrapolation of the last value, the use of a deterministic trend or the application of an advanced time series model are examples for applicable methods. Another possibility is estimating the future cash flow based on pro forma financial statements. Regarding the application of cash flow modeling and forecasting in reality, the fundamental method is mostly the standard method used in real-life applications.[91]

The application of cash flow models based on a fundamental analysis has one important drawback: The obtained future cash flows are normally point estimates. The calculated NPV based on these cash flows will then also be a point estimate, providing no information on the uncertainty of the future cash flows and of the NPV.

To overcome this drawback risk analysis methods can be applied to gain insight into the risks of a capital investment. From a theoretical point of view, the use of risk analysis allows the testing of the robustness of the estimated cash flows. The following methods are suggested by the financial literature for this task:

1. Sensitivity analysis,

2. Scenario analysis, and

3. Simulation analysis.

A sensitivity analysis measures the effect of changes in one of the input parameters on the estimated future cash flows.[92] The scenario analysis allows the simultaneous manipulation of several of the input parameters and the quantification of the impact. Thus each scenario results in one cash flow. A simulation analysis is based on a random manipulation of all input parameters. As a result it yields a probability distribution of the future cash flows.

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[90]Cf. Brealey et al. (2007) for a discussion of the potential problems in the determination of the relevant cash flows of a project.

[91]Cf. Kaka (1996) for a discussion of cash flow forecasting based on a simple cash flow model.

[92]Cf. Hwee & Tiong (2002) for an application of a scenario analysis in the context of a computer based cash flow forecast model.

The use of sensitivity analysis on all input parameters allows the identification of the input parameters which have the most influence on the output. The calculation of various scenarios within the scenario analysis allows the estimation of the impact of certain input parameter combinations on the output. Mostly three scenarios – called a base case, a worst case, and a best case – based on input parameters mirroring less or more optimistic future expectations are calculated. The base case scenario is the most likely scenario. Simulation analysis allows the quantification of probability distributions of the output as it "uses a random selection of scenarios (likely as well as unlikely) to generate information".[93]

Sensitivity and scenario analyses are often used in real-life applications. The sensitivity analysis is seen as the most popular method in applied work.[94] However, both methods have significant drawbacks. The sensitivity analysis bears the problem that it focuses on only one input factor; it ignores interactions among the input factors and combined effects. The scenario analysis usually ignores correlations between the single input parameters as well.[95] Furthermore, not every possible future state is taken into consideration and no probabilities for the single scenarios are available; in particular the worst and best case scenario do not provide information on the probability of outcomes in these (extreme) ranges.

Figure 2.6 illustrates the drawback of valuation results obtained through the scenario analysis method. These results are compared with results obtained through simulation analysis. The y-axis of the graph displays the probability, the x-axis the estimated cash flow. The three scenarios normally provided in a risk analysis are depicted in figure 2.6 as well. In addition, two probability distributions of the cash flow, obtained by simulation analysis, are contained in the figure.

When comparing the results obtained by the scenario analysis with the two probability distributions it stands out that in the case of the first distribution the results seem to be quite reasonable. The base case is around the mean value of the distribution and the worst and best case are located near the left and right boundary. However, in the case of the second distribution both extreme scenarios correspond to cash flow outcomes that are in the extreme tails of the distribution, being not very probable. Thus, when the results of the scenario analysis are used in the case when the real distribution of the cash flow equals the second distribution it is to assume that the risks, and the potential profit chances, are by far overstated.

Despite this apparent advantage of simulation analysis this method is used sparsely in real-life applications. Except for financial institutions using highly advanced mod-

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[93] van Groenendaal & Kleijnen (2002), p. 9.
[94] Cf. van Groenendaal (1998), p. 202.
[95] Cf. Balcombe & Smith (1999), pp. 118-119.

Figure 2.6
Scenario Analysis versus Simulation Analysis
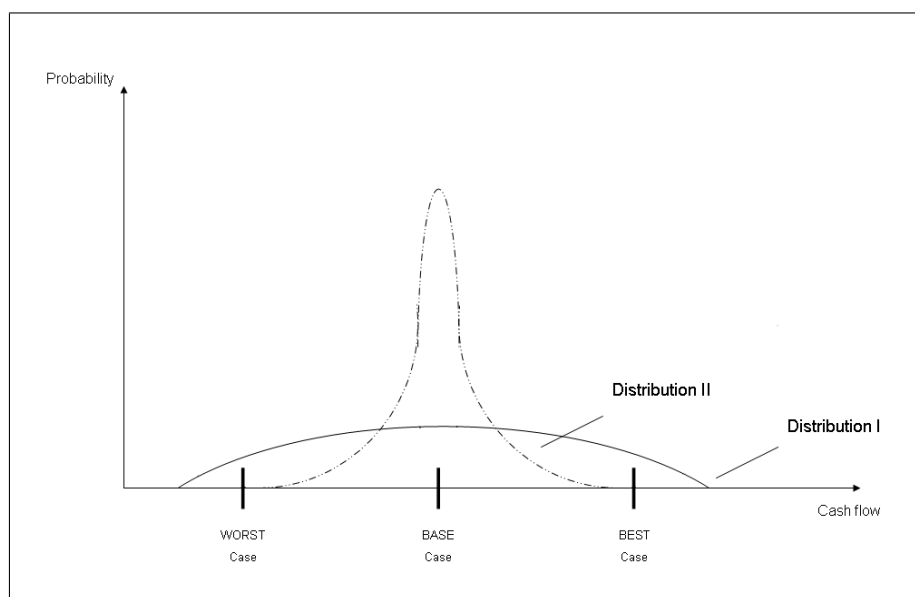
Source: Own work.

els based on simulation analysis to value derivatives contracts and other complex financial products, the proliferation of simulation analysis is low. This is probably due to the fact that this method is seen as too complex and not too easy to implement in standard software packages.[96] Also it can be presumed that an average manager is reserved towards stochastic modeling and has a lack of understanding this method.[97] However, the advantages of the simulation analysis compared with the other two methods are significant. Through the generation of probability distributions this method uses all available information and provides the most meaningful valuation result.

2.1.2.5 Stochastic Cash Flow Modeling

Stochastic modeling is based on repeated random sampling, i.e. the repeated drawing of random variables or numbers[98], with the aim to construct a probability distribution of the output of interest. Monte Carlo simulation (method) and the above

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[96]In real-life applications, mostly Microsoft Excel is used for cash flow modeling. In principle it is possible to develop a stochastic cash flow model within Microsoft Excel. However, it is not really applicable for meaningful computations due to its low computation power.

[97]Cf. Kwak & Ingall (2007), p. 46.

[98]Random numbers are numbers that exhibit statistical randomness. Cf. chapter 3 for a discussion of a potential computational procedure to obtain random numbers.

stated term simulation analysis are commonly used as synonyms.[99] I will use the term stochastic modeling in this dissertation. Since I intend to focus on the stochastic modeling of cash flows I do not discuss stochastic modeling in general; I focus on stochastic cash flow modeling.

Stochastic cash flow modeling refers to the forecasting of future cash flows with the aim of obtaining probability distributions of the cash flows at some future point-in-time. The main advantage of this method is the calculation of probability distributions instead of point estimates. In addition, this method uses almost all available information.

Stochastic cash flow modeling can simplified be seen as consisting of three steps:[100]

1. the specification of the cash flow equation and the input factors,

2. the simulation of future input factor values and cash flow values, and

3. the aggregation of the results to a probability distribution.

The specification of the input factors is based on the underlying cash flow equation that is used in the second step to calculate the single cash flows. It has to be decided which input factors are deterministic and which stochastic. Normally, the mean and the variance of the stochastic input parameters are defined, whereat most input parameters (due to simplification issues) are characterized by a normal distribution. In addition, but not necessarily, correlations between the single input parameters can be specified. A possibility to obtain reliable parameters estimates is to conduct an expert survey.[101] Another possibility is a time series analysis of the historical time series and a forecast of the relevant parameters. The advantage of the time series framework is the possibility to directly address the correlation structures within the input parameters.[102] I will discuss the input parameter specification in chapter 3 and the impact of correlations on the modeling results in chapter 5.

The underlying cash flow equation specifies the relationship between the input factors and the cash flow. The calculation of the cash flow is based on the repeating random combination of the input parameters. Hacura et al. (2001) state that "during the simulation process, random scenarios are built up using input values for the project's key uncertain variables, which are selected from appropriate probability distributions. The results are collected and analyzed statistically so as to arrive at a probability distribution of the potential outcomes of the project and to estimate

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[99]Monte Carlo refers to the famous state near France, known for its casinos. In a nice way the term points out that the component chance is playing an important role within this method.

[100]For a discussion of the risk analysis process cf. for example Backhaus et al. (2003).

[101]Cf. Hughes (1995), p. 180.

[102]Cf. Hui et al. (1993), p. 270.

Figure 2.7
A Probability Distribution Obtained by Stochastic Cash Flow Modeling
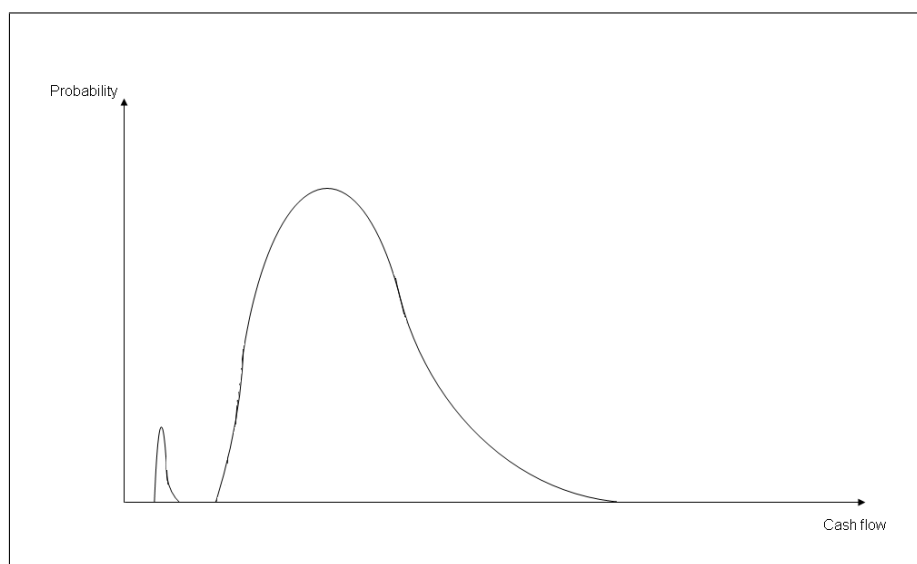
Source: Own work.

various measures of project risk".[103] The appropriate probability distributions of the forecasts of the input parameters are based on the provided specifications of the mean levels, variances, and correlations. The forecast of the future probability distribution function of all factors that influence the cash flow is a critical task. It will be discussed in the next chapter.

Finally, the aggregation of the single cash flows to a probability distribution yields a result similar to the example shown in figure 2.7. The y-axis displays the probability, the x-axis the cash flow.

The probability distribution in figure 2.7 is similar to a lognormal distribution, a distribution commonly used in finance.[104] However, the elevation on the left side in the probability distribution depicts one of the advantages of stochastic cash flow modeling, namely the possibility to model non-analytical probability distributions. A constellation resulting in the probability distribution shown in figure 2.7 would, for example, reflect the introduction of political risks. The assumption would be that a certain (small) probability exists every year that the project must be stopped due to a change of the political or regulatory environment. The results would lead to an extreme low, but still positive, cash flow in this year.

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[103]Hacura et al. (2001), p. 551.
[104]Many asset models assume that asset returns follow a geometric Brownian motion. This assumption results in a lognormal distribution of the asset prices. Cf. Hull (2008) for a further discussion.

The advantages and drawbacks of stochastic cash flow modeling are summarized below:

First, stochastic cash flow modeling overcomes the drawback of point estimates obtained by other risk analysis methods. By random sampling from several probability distribution functions of the input parameters a probability distribution of the cash flows at some future points-in-time is obtained; all possible future states are covered. The obtained probability distributions allow the quantification of the probabilities of certain future events. Thus stochastic cash flow modeling is, as stated by Kwak & Ingall (2007), "an extremely powerful tool when trying to understand and quantify the potential effects of uncertainty of the project".[105] Second, stochastic cash flow modeling is helpful when comparing capital investments with similar mean NPV but different risk structures; the obtained probability distributions of the cash flows and of the NPV allow to take more informed investment decisions.

However, this method also has several drawbacks.[106] First, stochastic modeling depends on accurate parameter forecasts and in particular on an accurate specification of the correlation structure between the input factors. Even small deviations of the input can have a significant effect on the results. Second, the complexity of the accurate specification of all input parameters is high, in particular when the correlation structure must be specified. Third, the necessary computing power to complete the stochastic modeling can be immense.[107] Fourth, easy to handle software tools are still rarely available. In addition, stochastic modeling should only be used when analytical solutions are not available.[108]

Hess & Quigley (1963) were the first to apply stochastic modeling in finance.[109] Hertz (Hertz (1964a), Hertz (1964b)) suggested that employing simulation techniques instead of single-point estimates of future income and expenses is superior when appraising capital expenditure proposals under conditions of uncertainty. The author argues that potential risks are identified more clearly and hence the expected return is measured more accurately. Smith (1994) outlines how simulations may assist managers in choosing among different potential investment projects. Spinney & Watkins (1996) apply stochastic modeling as an approach for integrated resource

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[105]Kwak & Ingall (2007), p. 49.

[106]Cf. Nawrocki (2001) for a discussion of the problems with Monte Carlo simulation.

[107]However, this problem is due to advances of the computer technology over the past decades to become less important.

[108]Cf. Nawrocki (2001), p. 93.

[109]The first documented application of stochastic modeling was performed for nuclear reaction studies in the Los Alamos National Laboratory (Metropolis & Ulam (1949), Metropolis (1987)). Hammersley & Handscomp (1964), followed by Glynn & Witt (1992), were the first to discuss the relationship between accuracy and computational complexity of Monte Carlo simulations. Since the Monte Carlo simulation is computationally highly intensive and hence reluctant on fast calculating machines, its application for the solution of scientific problems significantly rose as the costs for powerful processor decreased dramatically over the last two decades.

planning at electric utilities. They find that this approach offers advantages over more commonly used methods for analyzing the relative merits and risks embodied in typical electrical power resource decisions, particularly those involving large capital commitments. More recently, Kwak & Ingall (2007) discuss stochastic modeling for project management and conclude that it is a powerful tool to incorporate uncertainty and risk in project plans.

2.1.3 Project Finance Valuation

2.1.3.1 Project Finance Specifics

The strong dependence of the debt and equity providers on the project's cash flow is the key element of project finance elaborated in the sections above and elementary for the motivation of this dissertation. Though this is also true for equity providers when investing in differently financed projects, this situation is not common to debt providers. The partial takeover of business risk by the debt providers in project finance forces them to apply valuation techniques different to those in the traditional loan process. The main focus is on the forecast of the expected future cash flows. An appropriate forecast becomes critical for the realization and the success of a project finance investment.[110] The fact that the physical assets and future cash flows of project are of little value in the case of a project failure intensifies the situation.

The traditional loan process focuses on the lending company and not the project for which financing the loan is required. For the estimation of the company's creditworthiness the debt providers normally collect fundamental data (capital structure, profitability, etc.) on the company and calculate financial ratios, e.g. the financial leverage or the cash-to-debt ratio. Based on these historical measures a prognosis of the future financial situation of the company is made and the risks regarding the loan repayment are evaluated. The default probabilities estimated within this process concern the company and not the financed project.[111]

The characteristics of project finance, namely the non-recourse character of the debt, the foundation of the SPV with the sole aim of conducting the capital investment and the usually high specificity of the project, result in a situation for which historical data are not available. Thus, an evaluation of the capital investment based on the future cash flows is the only possibility. The creditworthiness of the sponsors is not of interest but rather the prospect of success of the capital investment.

An important advantage of project finance considering the valuation process is the

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[110]Cf. Böttcher & Blattner (2010), p. 3.

[111]A standard approach for the estimation of the default risk is the use of a commercial credit rating and the comparison with the historical default rates in the corresponding rating class.

creation of the SPV and the limited economic life of the project. This allows an evaluation of the project on a stand-alone basis.[112]

Most cash flow models used in reality are based on a fundamental analysis. However, the capabilities of stochastic cash flow modeling are significant, both from a theoretical and from a practical perspective. Thus, although stochastic modeling is rather more complex, it is the appropriate method for a detailed analysis of a capital investment; other techniques use simplifications that may substantially bias the outcome. The main advantage of stochastic modeling compared to other risk analysis methods is its ability to quantify the ex ante default probabilities.[113]

I aim to apply stochastic cash flow modeling in this dissertation in the context of project finance to quantify both the default probability (relevant for equity and debt providers) and the expected profitability of the capital investment (relevant for equity providers). Furthermore, cover ratios which are of high interest to the debt providers, can and will be calculated based on the probability distributions of the future cash flows. In the following I discuss the (capital) point of views and its specifics individually.

In reality, it is intended that – in the optimal case – the future (forecast) cash flows are sufficient for the timely repayment of the interest and principal and an appropriate – risk-adjusted – return for the sponsors.

2.1.3.2 Debt Perspective

Not only the approval but also the pricing of a project finance loan depends on the default probability and the level of variability of the future cash flows.[114] Thus, the quantification of the default risk and of the cash flow variability is of highest priority for the debt providers. A minimization of these measures through risk management is targeted.[115] Furthermore, it is of high importance for the debt providers to determine whether the expected cash flows are sufficient for the interest and principal payments in every period.[116] The methods applied for this purpose can be grouped in static and dynamic methods.

Cover ratios are the static methods mainly applied by debt providers in the case of project finance investments. In general, a cover ratio is defined as the quotient of (cash flow) inflow measure and a measure related to the debt capital. For the

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[112]Cf. Borgonovo et al. (2010), p. 227.

[113]Cf. Werthschulte (2004), p. 2.

[114]Cf. Corielli et al. (2008), p. 4.

[115]Cf. section 2.1.1.5 for a discussion of the importance of risk-sharing within a project finance transaction.

[116]Cf. Werthschulte (2004), pp. 43-44.

calculation of a cover ratio the application of a fundamental cash flow model is sufficient, i.e. no stochastic cash flow modeling is required. However, the calculation of cover ratios based on probability distributions of one of the input measures is possible as well. In this case the mean value of the probability distribution is used as a point estimate for the cover ratio calculation. The whole information contained in the probability distribution can also be used as discussed below.

The following three cover ratios are frequently used for project finance investments:

1. Debt service cover ratio (DSCR),

2. Loan life cover ratio (LLCR), and

3. Project life cover ratio (PLCR).

The definitions of these ratios are not consistent in the literature. I hence provide a general definition.

I define the DSCR as:

$$DSCR_t = \frac{CF_t}{DRA_t} \tag{2.3}$$

with $DSCR_t$ the DSCR in period t, CF_t the (operative) cash flow in period t and DRA_t the debt repayment amount (DRA), i.e. interest + principal, in period t.

The LLCR and PLCR are defined as:

$$LLCR = \frac{NPV \ all \ cash \ flows \ over \ lifetime \ loan}{Loan \ Amount} \tag{2.4}$$

$$PLCR = \frac{NPV \ all \ cash \ flows \ over \ lifetime \ project}{Loan \ Amount} \tag{2.5}$$

When these ratios are calculated within a risk analysis the debt providers mostly demand that the ratios never decline below certain critical values during the whole lifetime of the loan (project). The critical values depend on the risk, industry, and other specifics of the project. After the granting of the loan, minimum values of the cover ratios are often specified as covenants.

For the DSCR, for example, a continuous value above one is critical to guarantee the ability of the SPV to pay the interest and principal on time. A high DSCR value also indicates a low default probability. Thus, it can be assumed that higher DCSRs imply lower interest rates for the granted debt capital. The DSCR is seen as the central ratio in a project finance investment and usually a DSCR of at least 1.3 is expected.[117]

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[117]The assumed minimal value of 1.3 for the DSCR is based on discussions with project finance

The DSCR is a period specific ratio. The other two ratios, namely the LLCR and the PLCR[118], affect the whole lifetime of the loan (project). Both ratios aim to determine the project's ability to repay the loan, only the timeframes are different. A main drawback of these ratios is that the chronological order of the cash flows is ignored. The PLCR does not even indicate whether the sum of the cash flows over the lifetime of the loan is sufficient for the whole repayment.

Further cover ratios are used in project finance investments. I intend to implement four additional cover ratios in the project finance valuation tool that is developed within this dissertation.

First, two interest coverage ratios are implemented:

$$EBIT\ interest\ coverage_t = \frac{EBIT_t}{Interest_t} \tag{2.6}$$

$$EBITDA\ interest\ coverage_t = \frac{EBITDA_t}{Interest_t} \tag{2.7}$$

with $EBIT_t$ the earning before interest and taxes (EBIT) in period t and $EBITDA_t$ the earning before interest, taxes, depreciation and amortization (EBITDA) in period t. $Interest_t$ is the interest expense in period t.

Second, I implement two total debt ratios. One with the funds from operations (FFO) in the numerator

$$FFO/Total\ Debt = \frac{Funds\ from\ operations}{Total\ Debt} \tag{2.8}$$

and one with the free operating cash flow (FOCF) in the numerator

$$FOCF/Total\ Debt = \frac{Free\ operating\ cash\ flow}{Total\ Debt}. \tag{2.9}$$

The reader is referred to standard literature on financial statement analysis for further details on these ratios.[119]

The main drawback of cover ratios which are based on point estimates of the (cash flow) inflow measure is the limited information value of the results. A high DSCR, for example, only indicates that a default is unlikely. It is not possible to quantify the remaining default probability. Stochastic cash flow modeling can overcome this drawback though the providing of probability distributions of the cover ratios.

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investors.

[118]The PLCR is also known as the Net Present Value Cover Ratio (NPVCR) in the literature; cf. for example Werthschulte (2004), p. 45.

[119]Cf. for example Penman (2007).

Dynamic methods applied for the valuation of project finance investments include the three risk analyses methods discussed above. Since I have already discussed these methods I focus in the following on the advantages of stochastic modeling for project finance as it is applied in the context of the later introduced project finance valuation tool.

The advantages of stochastic cash flow modeling in project finance valuation are: First, the obtained probability distributions can be used to evaluate the effects on the cover ratios, i.e. a probability distribution of the cover ratios can also be derived. The above discussed drawback of cover ratios based on fundamental analysis is corrected. Second, after calculating of the probability distributions of the cash flows in some future points-in-time[120], the debt providers will be primarily interested in the quantification of the downside risks. A method to quantify this risk is the cash-flow-at-risk approach[121], a measure similar to the widely used value-at-risk.[122] Through the quantification of certain confidence levels (mostly 1%, 5%, and 10%) this method enables the quantification of the maximum shortfall. Third, the probability distributions of the future cash flows obtained through stochastic cash flow modeling allow the quantification of the probabilities of cash flows becoming negative in a certain period. Based on these measures the ex-ante default probability can be estimated. This is one of the main advantages of stochastic cash flow modeling.

Overall the main advantage of the use of stochastic cash flow modeling from a debt provider's point of view is the fact that it allows the exact quantification of certain risks. However, the user of this approach should always be aware that the results are based on assumptions. So even if the results seem to be exact, they need to be interpreted with caution. Two main aspects must be kept in mind. First, stochastic modeling assumes – similar to the most applied modeling methods – that future developments can be derived from past values. Second, the results of stochastic modeling are very sensitive to the input parameters. A misspecification of only one of the normally dozens of input parameters has the potential to significantly bias the results.

2.1.3.3   Equity Perspective

As stated by Graham & Harvey (2001) the NPV and IRR method are the two valuation approaches for equity investments most often used in real-life applications.[123]

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[120]The future points-in-time ideally correspond to the dates when interest and principal payments by the SPV are due.

[121]Cf. Andren et al. (2005) for an overview on cash-flow-at-risk approaches.

[122]However, the cash-flow-at-risk is a top-down approach as the value-at-risk is, in general, a bottom-up approach; cf. Chiu (2007), p. 2.

[123]Cf. Graham & Harvey (2001), p. 196.

Discussions with practitioners active in project finance confirm that these two methods are also mainly used by sponsors in project finance investments. Thus, I assume that the maximization of the NPV or rather the IRR of a project is in the scope of the sponsor's analysis in project finance. In reality, the decision to invest is often dependent on the reaching of certain thresholds in the measures.

As the sponsors are mainly interested in the estimation of the profitability of a project they will generally use – similar to the debt providers – a cash flow model to estimate the future cash flows. The expected NPV and IRR will then be calculated based on the cash flow projections. Discussions with practitioners active in project finance confirm the assumption that mainly fundamental cash flow models are used in reality. Sensitivity and scenario analysis are the risk methods which are generally applied. However, as it was already discussed above, this dissertation focuses on the application of stochastic cash flow modeling. I believe that the advantages of this method significantly exceed its disadvantages.

The probability distributions of the NPV and of the IRR are calculated based on the estimated future cash flow distributions. In addition, the cash-flow-at-risk is of interest. The calculation of the cash-flow-of-risks allows sponsors to quantify the potential shortage of cash flows in certain periods (at a certain level of confidence). The sponsors can use this measure to estimate the probabilities and amounts of potential reserve liabilities.

2.1.3.4 Related Literature

Considering its importance in practice, the academic literature on project finance is surprisingly sparse with only a few relevant papers being published in recent years.[124] Most of these papers focus on qualitative, organizational, or legal aspects of project finance. Regarding the valuation of project finance the number of publications is even sparser. To my best knowledge only two published papers by Esty (1999) and Gatti et al. (2007) and one working paper by Dailami et al. (1999) highlight the issue of (quantitative) cash flow modeling in the context of project finance.

Esty (1999) discusses methods for improving the valuation of project finance investments from an equity provider's point of view. To achieve this goal, the author suggests both advanced discounting methods and valuation techniques. The author discusses the arising problems from the fact that the leverage of a project finance investment changes over time, resulting in the fact that the use of a single discount rate over the whole lifetime of the project is inappropriate for the valuation. Furthermore, the problems with the accurate measurement of leverage, i.e. the question

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[124]Cf. Esty & Megginson (2001) for an overview on the academic literature on project finance.

whether book or market values of debt are appropriate when estimating the value of debt, are addressed. In addition, the author discusses the use of Monte Carlo simulation to analyze the uncertainty of cash flows and the advantages of real options analysis. However, the focus of the work is on the improvement of the discount rate estimation and not the cash flow forecasts. Thus, besides discussing important elements for valuation, the author does not present a self-contained model that enables equity providers to calculate either the profitability of a project finance investments or the expected probability of a project default.

Dailami et al. (1999) introduce in their working paper a computer-based risk management tool with the focus on infrastructure project finance transactions. The tool is capable of analyzing the impact of certain risk factors on a project. The authors aim that the tool raises awareness and expertise in the application of techniques related to risk management. The developed tool is able to generate probability distributions of the project's NPV, IRR, and other key decision variables. To illustrate the capabilities of the tool the authors apply it to a coal-fired facility.

Gatti et al. (2007) aim to estimate the value-at-risk of project finance investments. This risk measure is in particular of interest for banks that are involved in the project finance business, rating agencies, and regulators. A value-at-risk measure is intended to support the process of credit risk estimation in a project finance investment. The authors suggest a model that is based on Monte Carlo simulation to measure the value-at-risk. The authors describe the process to model the cash flows of a project in four steps, namely (i) the definition of a suitable risk assessment model, (ii) the definition of the project variables and key drivers, (iii) the estimation of the input variables and the respective value distributions and the accounting for correlations among the variables, and (iv) the modeling of the project cash flows, the calculation of the outputs, and the valuation results. In addition, Gatti et al. (2007) discuss the definition of default risk in project finance and how a loss distribution could be derived. The focus of the authors is mainly on the implication for the lenders.

2.2 The German Electricity Wholesale Market

The liberalization of the German electricity market started around 15 years ago. One of the first visible outcomes was the foundation of two electricity exchanges which merged to the EEX in 2002. The EEX is, like every other electricity exchange, a wholesale market. Thus, it is characterized by a limited number of market participants and relatively low liquidity levels. These characteristics pose questions regarding market efficiency and the reliability of the established prices.

In this section I examine both the German electricity market and the German electricity exchange. I discuss the liberalization of electricity markets and address the electricity market reform in the European Union and the liberalization process of the German market. The establishment of electricity exchanges as a result of the liberalization is presented. I subsequently summarize the stylized facts on the commodity electricity and on electricity prices. In particular, the unique characteristics of electricity prices are crucial for the empirical analysis of this dissertation. I then focus on the German electricity market and examine the market size, the market design, and the market structure. I distinguish between the five market segments which are or were in existence, namely the intraday market, the block contract market, the day-ahead market for the spot market, and the futures market and the options market for the derivatives market. In addition, the evolution of the retail electricity price is discussed. At the end of the section, I address the EEX and its specifics. I devote considerable attention to the individual market segments, the traded products, and the trading process. Moreover, the market participants are examined and the evolution of the wholesale electricity price over the last years is discussed. Furthermore, potential drivers of the observed evolution are illustrated.

This section aims to answer the following three key questions:

- What are the unique characteristics of the commodity electricity and of electricity prices?

- What is the current structure and size of the German electricity market?

- What are the fundamentals of trading on the German electricity exchange and why are the established prices so important?

2.2.1 Liberalization of Electricity Markets

2.2.1.1 Motivation and Market Reform

The liberalization of electricity markets in Europe started in Norway and in Great Britain at the beginning of the 1990s. The beginning of the liberalization process was based on the insight that markets are a better allocation mechanism than the then existing system, a highly regulated market with monopolistic structures on the supply side.[125] The aim was the introduction of free markets and the transformation of the cost-based regulation into a market-oriented price formation.

Prior to the liberalization, electricity markets all over the world were characterized by regulation and by lack of competition. The supply side consisted mainly of state-owned, vertically-integrated companies or regulated private companies, often monopolists within their supply area.[126] Based on the lack of public markets and competition the pricing mechanism was intransparent and often derived from a cost-based approach. The results were missing incentives for cost minimization in both the electricity generation and the distribution process. Higher costs were – after an approval of the regulatory bodies – simply passed on to the customers.[127] The regulatory bodies mainly aimed at ensuring stable electricity supply; minimal costs were not in the focus.

The stated rationale for this market structure was, together with the natural monopoly character of electricity transmission, the observable high economies of scale in the electricity industry. Over the years this established the opinion that this market structure is legitimate and the best available option.[128] In addition, the security of supply is seen as crucial for the development of an economy; hence governments generally try to keep a certain level of control over the national electricity market.[129] However, supporters of liberalization tried to unbundle this industry by asking whether there are at least parts within the value chain where competition is possible.[130]

The third election victory of the Thatcher government in 1987 put the privatization of the British energy industry onto the political agenda, resulting in the passage of the Electricity Act in 1989; a first and fundamental step into a competitive market. Shortly after, the Norwegian Parliament started a reform of the electricity market which was implemented in 1991.[131]

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[125]Cf. Weigt (2009) for a recent review of the worldwide liberalization of electricity markets.
[126]Cf. Weigt (2009), p. 3.
[127]Cf. Kramer (2002), p. 1.
[128]Cf. Weigt (2009), p. 3.
[129]Cf. Müller-Merbach (2009), p. 6
[130]Cf. Wawer (2007), p. 5
[131]Cf. Weigt (2009), pp. 4-6.

Based on these markets' experience with liberalization, the European Commission began reconsidering its electricity policy. The liberalized market gradually became the new paradigm. The actual liberalization process in Europe began with the Electricity Directive 96/92/EC in 1996. The directive required the national governments to develop plans for the liberalization of their respective markets by February 1999.[132] The directive included the introduction of a freedom of choice of the electricity supplier for a certain share of customers. In addition, it proposed three potential third-party access models to the transmission networks. It also required the administrative unbundling of supply, generation, and network activities.[133] The intention was to gradually open the markets and in particular to provide third-party access to the networks, an obligatory condition for competition.[134]

In 2001, the European Council concluded further measures were necessary, as the outcome of the first directive had been widely regarded as unsatisfactory. The European Council thus approved a second directive, the Electricity Directive 2003/54/EC. This directive reduced the freedom of choice for the national governments and shortened the deadlines. According to the second directive, the market for non-household electricity consumers and for all consumers had to be liberalized by certain point-in-times.[135]

2.2.1.2 Liberalization of the German Market

Prior to the liberalization of the German market, the regulation had been based on the 1936 federal Energy Industry Act, the Energiewirtschaftsgesetz (EnWG).[136] The preamble of the EnWG disclosed the law's intention by stating that the damaging economic drawbacks of competition must be avoided in the electricity industry in order to secure cheap electricity supply. The results of the regulation were closed supply areas and an electricity market being a private sector under state supervision.

In the German electricity market the starting point of the liberalization process was the first European Electricity Directive of 1996 which was implemented in the federal Energy Industry Act in 1998. The act's intention was to open electricity supply for competition. Main issues were – as requested by the European Commission – free selection of the electricity supplier for end consumers and the formulation of rules of third party access to the transmission networks.[137] However, the act allowed the industry a wide spectrum of choices of how to implement the required liberalization

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[132] Cf. Polo & Scarpa (2002), p. 18.
[133] Cf. Weigt (2009), p. 8.
[134] Cf. Krisp (2007), p. 38.
[135] Cf. Weigt (2009), pp. 8-9.
[136] Cf. Krisp (2007) for a discussion of the German electricity policy since the 1980s.
[137] Cf. Ockenfels et al. (2008), p. 4.

steps.[138] This freedom of choice resulted in an insufficient self-regulation of the market; the intended level of competition was not reached. Thus, after the second directive, the German government tightened the requirements.

One of the new measures was the establishment of a regulatory body, the Federal Network Agency (Bundesnetzagentur). The Federal Network Agency took up regulatory activity in the field of third party access and implemented rules for this procedure. The charged fees for the use of the transmission network by third parties, for example, are now subject to approval by the agency. Furthermore, the unbundling of the vertically integrated supply companies was demanded by law in 2005.[139]

2.2.1.3 Establishment of Electricity Exchanges

The liberalization process drove the need for marketplaces, resulting in the foundation of electricity exchanges. The foundation of the Nord Pool in Oslo in 1993 marks the introduction of the exchange trading of electricity in Europe.

Since the first Electricity Directive of the European Commission did not contain any specifications regarding the design of the electricity wholesale markets most trading took place in over-the-counter (OTC) markets at the beginning. However, due to the intransparency and slowness of these markets electricity exchanges were soon founded, in order to provide publicly available reference prices.[140]

In particular at the end of the last century, a multitude of national electricity exchanges were founded all over Europe. Figure 2.8 contains an overview of the electricity exchange landscape in Europe in 2007.

At the moment almost twenty electricity exchanges exist within the European Union. Figure 2.8 reveals that besides the Scandinavian countries almost every country has its own electricity exchange. The common electricity market of the Nordic countries – Sweden, Norway, Finland, and Denmark – located at the Nord Pool, is a first example for an international electricity market.[141] First steps in the direction of a market coupling on an international level are observed. Examples are Belgium, France, and the Netherlands where a (day ahead) market coupling was recently introduced.[142]

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[138]Cf. Weigt (2009), p. 11.

[139]Cf. Weigt (2009), p. 11.

[140]Cf. Ockenfels et al. (2008), pp. 11-12.

[141]The integration of the national Nordic markets to a joint Nordic market had taken place between 1993 and 2000. In 1993 the Nord Pool started operation for the electricity market of Norway; in 1996 it was joined by Sweden and in 1998 by Finland; in 1999 and 2000 the western and eastern part of Denmark, respectively, completed the joint market.

[142]Cf. Meeus et al. (2006) for a discussion of the market integration in France, Belgium, and the Netherlands.

Figure 2.8
Electricity Exchange Landscape in Europe in 2007
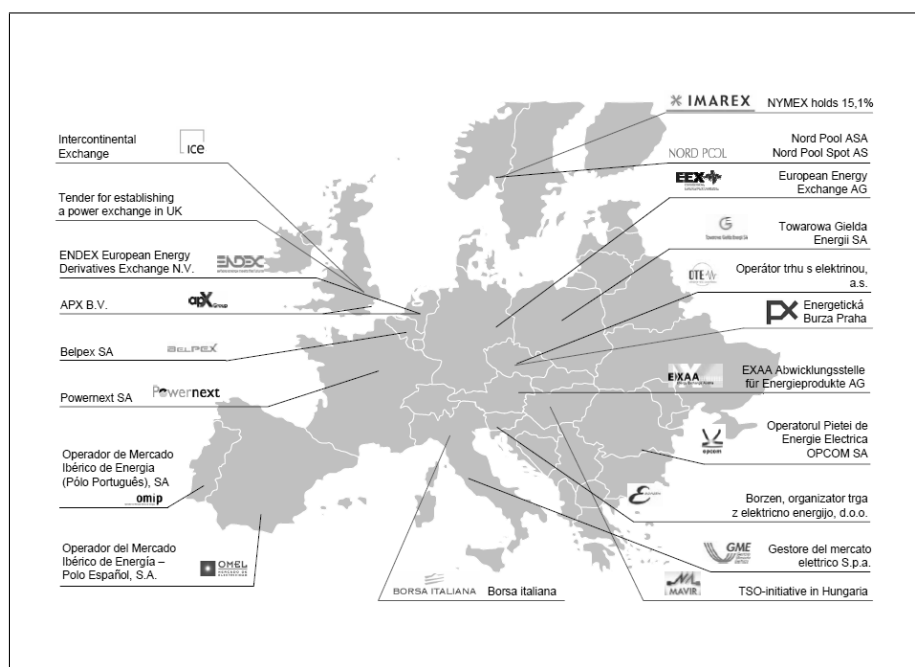
Source: Taken from Menzel (2007), p. 10.

On most electricity exchanges trading takes place in spot and futures markets. Option markets also exist but the liquidity in these markets is normally very low. Contracts with physical and financial settlement are traded on almost all exchanges. The main part of trading is observed in the futures markets, where the main part of the liquidity is observed in futures with financial settlement.[143] All electricity exchanges serve as wholesale markets.

Initially the prices on the single electricity exchanges were largely independent and unaffected by events in neighboring electricity markets. However, a change of the situation could be observed over the last years. Empirical research suggests that the correlation between the markets is growing, even though the pace is differently evaluated.[144] In particular the market coupling efforts undertaken by the European Commission seem to strengthen the market integration.

The importance of the electricity exchanges and of the established prices is enormous as they establish a reference price. Assuming a sufficient level of liquidity in the exchange-based trading, no electricity buyer or seller will agree to a bilateral contract

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[143]Cf. section 4.4.1 for a discussion of the liquidity in the single market segments of the German electricity exchange.

[144]Cf. for example Armtrong & Galli (2005), Zachmann & von Hirschhausen (2008), Bundesnetzagentur (2010), and Bosco et al. (2010).

(disregarding the transaction costs) with a specified price below the actual exchange price. The electricity prices established on the exchange thus serve as reference prices for the whole electricity market.[145]

Due to the high number of national exchanges, many of them characterized by low liquidity, it is to assume that a consolidation of the electricity exchange landscape will take place in the next years. The cooperation of the EEX and the Powernext established in 2008 is one of the first examples for this process.[146]

2.2.2 Stylized Facts on Electricity and on Electricity Prices

The commodity electricity and the observed electricity prices exhibit unique characteristics which I discuss in the following; I distinguish between stylized facts on the commodity electricity and stylized facts on electricity prices.

2.2.2.1 Stylized Facts on Electricity

The following stylized facts on the commodity electricity are commonly found in the existing literature:

1. Non-storability,

2. Grid-bound transportation,

3. Regionalism, and

4. Independence of spot and forward markets.

Non-storability

Non-storability is the outstanding characteristic of the commodity electricity. From a technical point of view some storage technologies can be identified, e.g. pump water hydro plants or storage lakes. Pump water hydro plants are the only technology available to store electricity on a larger scale.[147] However, from an economic point of view it is assumed that electricity is not storable due to the high costs involved.

Most other unique characteristics of electricity are due to its non-storability. It is also the reason behind the necessity to generate and consume electricity simultaneously.

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[145]Cf. Ockenfels et al. (2008), p. 4.
[146]Cf. 2.2.4.1 for a discussion of this cooperation.
[147]Cf. Schill & Kemfert (2009), p. 3.

Grid-bound transportation

The transmission of electricity takes place in power grids. They are the only transport possibility for electricity on a larger scale. The grids often span over thousands of kilometers and require investments in the magnitude of billions of Euro. In particular the transmission over long distances requires special networks that are both costly and sensitive to external influences. The operation of the grids is difficult due to the fact that input and output always have to be balanced. An in-balance can lead to a collapse of the whole grid.

The grid-bound transportation is also the cause of another significant problem in electricity markets: transmission constrains or congestion. Congestion arises when a grid is operated at its physical maximum. No additional electricity can be then transported through this grid. The setting of rules about how to handle congestion is very important for electricity markets.[148]

Regionalism

Due to capacity restrictions the transmission of large electricity amounts over national borders is often difficult. Therefore, the available transmission capacity through the cross-borders cables is auctioned. This takes place in the form of options, the so called physical transmission rights (PTRs). A trader has to buy a PTR in order to be able to exploit price differences between two national spot markets. The PTR must normally be bought before the electricity prices are known; this implies taking over additional risk. The German power grid, for example, is connected through three high-voltage cross-border cables with the Dutch power grid.[149] Despite the auctioning of PTRs price differences between the markets seem to prevail.[150]

The lack of sufficient cross-border capacity is one of the reasons why despite the worldwide liberalization of national electricity markets an integrated single (European) electricity market still is not reached. The national markets are not coupled, consisting mainly of regional markets. One of the implications is that price changes in national market do not impact – at least in the short-term where arbitrage is not possible – the price in another market or region or vice versa.

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[148]Cf. for example Furio & Lucia (2009) regarding the Spanish market.

[149]Cf. Marckhoff (2009) for a discussion of the German-Dutch cross border market and the trading of PTRs.

[150]Cf. Andeweg et al. (2009) for a discussion of profitable trading strategies based on this observation.

Independence of spot and forward markets

The independence of the spot and forward markets is due to both the non-storability of electricity and the resulting non-existence of an arbitrage-relation. This characteristic is almost unique as the most asset and commodity spot and forward markets are linked by an arbitrage relation.[151]

The result of this characteristic is a loose relation between the spot and forward price, leading to an extensive research on price formation in electricity futures markets as it is discussed in the next section and in the empirical part of this dissertation. The loose relation, among other things, results in a low correlation between the spot and futures time series; this is even amplified through the high volatility and kurtosis of the spot prices as it is discussed below.

2.2.2.2 Stylized Facts on Electricity Prices

The following stylized facts on electricity prices are found:

1. Seasonality,

2. High Volatility,

3. Price spikes,

4. Mean reversion, and

5. Negative prices.

Seasonality

Seasonality on a daily, weekly, and yearly scale is observed in electricity price time series.[152] Climatic changes over the year, i.e. temperature fluctuations and varying numbers of daylight hours, lead to a seasonality on the demand side.[153] The demand is mostly higher in the winter. However, in certain regions a peak in the summer months due to increased use of air condition can be observed as well. Countries heavily relying on water power, e.g. the Scandinavian countries[154], also face seasonality on the supply side due to the fluctuating level of water reservoirs. Both effects

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[151]Examples for other non-storable commodities are difficult to find as almost every commodity is storable to some extent. Cattle, eggs and pork bellies are examples for commodities with limited storability.

[152]Regarding the German market, the daily and weekly seasonality is significant. Regarding the yearly seasonality empirical evidence is mixed. As, for example, discussed by Weron (2006) there is no clear evidence for a yearly seasonality in the German market.

[153]Cf. Weron et al. (2004), p. 2.

[154]Around 50% of the electricity generated in the Nord Pool is produced by hydro plants; cf. Bask & Widerberg (2009), p. 279.

lead to a yearly seasonality. The weekly seasonality is explained by the high share of industrial electricity consumers[155] that do not demand electricity on weekends and non-working days, i.e. by changing business activites. The daily seasonality is related to the different demand patterns during night and day, again mainly caused by the industrial consumers.

Not only the mean but also the volatility of electricity prices seems to be time-dependent.[156]

High Volatility

Electricity prices are characterized by volatilities merely observed in other markets. Daily volatilities over 40%[157] are observed; volatilities of two orders of magnitude higher than observed for other asset price time series are common.[158] The non-storability of electricity leads to a situation where variations in supply and demand almost have real-time influence on the electricity price. In particular changes on the supply side translate into high increases of the electricity price.

Furthermore an "inverse leverage effect" is observed, indicating that the volatility of electricity prices tends to rise more strongly after price increases than after price decreases.[159]

Price spikes

Price spikes are narrowly linked to the high volatility. Price spikes are a sudden increase of the electricity price, often more than tenfold. These high prices tend to remain for hours, at the highest to days, and return afterwards to normal price levels.[160]

As no inventories of electricity can be used to dampen shocks in the supply or demand the results of these shocks are severe.[161] Another important factor favoring price spikes is the inelasticity of the demand. The fatalist price spikes are hence observed after power plant outrages, when a significant part of the supply side disappears almost immediately.

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[155]The distribution over the three largest electricity consumer groups in the German market is as follows: industry consumers (47%), households (26%), and commercial consumers (14%). Together with commercial and other consumers almost three fourth of the total electricity consumption in Germany is due to non-household consumers; cf. Bundesministerium für Wirtschaft und Technologie (2010) for the data.

[156]Cf. Weron (2008), p. 1100.

[157]Cf. Ullrich (2009) for a discussion of the importance of data frequency when analyzing time series characteristics of electricity prices.

[158]Cf. Weron (2006), p. 101.

[159]Cf. Knittel & Roberts (2005), p. 793.

[160]Cf. for example Seifert & Uhrig-Homburg (2007) for a discussion of price spikes.

[161]Cf. Marckhoff (2009), p. 1.

One result of the price spikes is a non-Gaussian distribution of electricity prices. A significant heavy tail is observed and the resulting distributions are right skewed. Regarding the electricity price modeling and forecasting price spikes play an outstanding role on the short-term time scale. On a long-term scale, on the other side, they are due to the short lifetimes of minor interest.

Mean reversion

Mean reversion refers to the characteristic of electricity prices to revert in the mid- and long-term to a long-term average price.[162]

The rationale behind the mean-reversion of electricity prices is the (long-term) adjustment of the supply to the demand, resulting in a convergence of the electricity price to the cost of production.[163] Furthermore the mean reversion of the weather as a dominant driver of the equilibrium electricity price could lead to a mean reversion of the prices as well.[164]

Negative prices

Another characteristic of electricity price time series is the occurrence of negative prices. This is due to the costly and sometimes technically not even possible shutdown of power plants in the short-term. A power plant shutdown is associated with high costs. In certain hours it can hence be reasonable for a power plant operator to pay positive amounts to market participants who are willing to take the produced electricity from the network.

In such a case the buyer could be another electricity supplier who has the possibility to shut down his power plant at lower costs or in a shorter time period. The received electricity is then used to satisfy the existent delivery obligations instead of generating it oneself. The (simplified) gain of the trade is the received amount minus shutdown costs.

2.2.3 German Electricity Market

In this section, I address the German electricity market. First, I examine the market size of both the international and the national market.[165] Second, I discuss the

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[162]Cf. section 3.5.2 for a discussion of this time series characteristic.

[163]Cf. Cartea & Figueroa (2005), p. 314.

[164]Cf. Escribano et al. (2002), p. 4.

[165]All statistical data reported in this section are based on total electricity generation in the corresponding year. The data are obtained by the German Federal Ministry of Economics and Technology, the Bundesministerium für Wirtschaft und Technologie (BMWi); cf. Bundesministerium für Wirtschaft und Technologie (2009).

market structure of the German electricity market. Third, I address the structure of the supply and the demand side. Fourth, I illustrate the evolution of the electricity price over the last decade.

2.2.3.1   Market Size

Total world generation of electricity amounted to 19,855 TWh in 2007. The highest ratio of the generation was contributed by Asia, followed by North America and Europe. Regarding the European market, Germany (637 TWh) was the largest electricity generator, followed by France (570 TWh), and by Great Britain (396 TWh).

The German electricity market is both on the generation and on the consumption side the largest market in Europe. With its total generation of 637 TWh the German market is around ten percent larger than the French market and is equal to around 12% of the total electricity generation in Europe. However, when compared with the world market the German market accounts for only 3.2% of total worldwide generation. Compared with the two largest electricity producers in the world, the United States (22%) and China (17%), the size of the German market is relatively moderate.

Due to an under-proportional growth of the German market in relation to the total market the German market share on the worldwide market is supposed to further decline in the future. Over the time period 1990 to 2007, for example, the compounded annual growth rate of the world market was around 3.1%. The German market grew with an average growth rate of approximately 0.9% over this period.

2.2.3.2   Market Design

Two principal market structures are found in liberalized electricity markets. On the one side, the pool model as a centralized model, on the other side, the exchange model as a decentralized organization form of the market. The pool model is mostly implemented in English-speaking countries; the exchange model is deployed in all European countries except the British market.[166] In addition, bilateral trading (OTC markets) – mainly for forward transactions – is found in most national markets.

The German electricity market is organized based on the exchange model. It consists of a sequence of markets on which electricity for delivery in a certain time period is traded at different times. The main market is the wholesale market with its market

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[166]Cf. Grimm et al. (2008) and Ockenfels et al. (2008) for a discussion on the two market structures and how they are implemented in the largest European markets.

segments (intraday market, day-ahead market, and futures market). The German wholesale market is located at the EEX. The EEX is discussed in section 2.2.4.

The exchange model exhibits a central challenge: The co-ordination of the markets for generation, transmission, and balancing energy.[167] Regarding the German market, the transmission within the national borders is so far unproblematic since the capacity of the German power grid is sufficient.[168] The balancing energy market[169] (sometimes also control energy market) serves the purpose to secure the stability of the power grid. It is operated by the transmission system operators (TSOs). The TSOs are responsible for the permanent balance between electricity generation and demand in their control areas[170]; their assignment is to secure that the power frequency remains stable.[171] An unstable frequency mostly implies a breakdown of the grid. Parts of the balancing energy are auctioned on a daily basis, with the grid operators on the demand side and the power companies and electricity traders on the supply side.[172]

The value chain within the power sector is classified by thee broad levels: (1) generation, (2) transmission, and (3) distribution. The power plant owners, in Germany normally one of the four large utilities[173], are responsible for the electricity generation. The transmission of the electricity over the grids is organized by the TSOs. The fee for the transmission in the case of an inequality between power generator and owner of the TSO is approved by the German regulator, the Bundesnetzagentur.[174] In the majority of cases the distribution of the electricity is lastly performed by public services.

Regarding the importance of the wholesale market, it is to assume that similar to the time before liberalization still a high percentage of the supply contracts in the German market is characterized by long maturities and fixed prices.[175] Furthermore, it is to assume that a high percentage of the electricity that is traded between the generation units and the distributors has long-term fixed prices. However, it is also to assume that the market participants do not hedge all of their price risk. A certain percentage will be left open and bought short-term at the wholesale market at the

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[167]Cf. Ockenfels et al. (2008), p. 10.

[168]Cf. section 2.2.2.1 for a discussion of the electricity transmission over national borders.

[169]Thee different types of balancing power are distinguished, namely primary, secondary, and tertiary balancing power. The differences are the activation times and the durations of operation; cf. Flinkerbusch & Heuterkes (2010) for more details.

[170]The German market consists of four control areas. The Bundesnetzagentur recently postulated to pool these four control areas due to cost reduction potentials; cf. Bundesnetzagentur (2010).

[171]Cf. Flinkerbusch & Heuterkes (2010), p. 4713.

[172]Cf. for example Rammerstorfer & Wagner (2009) for a discussion of this procedure.

[173]Cf. the next section for a discussion of the structure of the supply side.

[174]Cf. for example Dieckmann (2008) for a discussion of the transmission process.

[175]Regarding the North American market Nakamura et al. (2006) report that about 50% of all electricity deliveries are still determined by bilateral forward contracts.

actual market price. The wholesale market price then serves as a decision foundation and the prices of new long-term contracts and the wholesale price converge. Thus, the wholesale market determines the whole market (in the long-term) as all contracts reflect the wholesale market price.[176]

2.2.3.3 Market Structure

In 2007 the total German generation capacity amounted to 137.5 GW. Anthracite (29.3 GW), lignite (22.5 GW), wind (22.2 GW), and nuclear power (21.3 GW) were the four fuels with the main ratio on the German total generation capacity.

When analyzing the German electricity capacity and generation statistics, the decomposition of the year's generated electricity shows that the ratios of one fuel on total capacity and on total generation can differ significantly. According to the official statistics nuclear power was the most important fuel in the German market in 2007. 27% of the total generation was due to nuclear power; lignite and anthracite followed by 26% and 22%, respectively. The electricity generation in Germany in 2007 was hence characterized by the use of fossil fuels and nuclear technology. The three fuels accounted for around three-quarts of the total electricity generation.

The available data further reveal that wind and water accounted for around 7% of the total generation. When compared with a combined share of 23% on the total generation capacity this number appears surprisingly low. However, the specifics of the electricity generation based on water and wind need to be taken into account to explain this wide gap.

In Germany water based electricity generation is almost solely dependent on pump water power plants. In these power plants electricity is first transformed in potential energy. Then it is transformed back to electricity. The costs of this technology are high. Thus, pump water power plants are, from an economic point of view, more a storage than a generation technology and tn reality mostly used in peak load hours. The electricity generation based on wind energy on the other side is very sensitive to the actual wind situation. A too light or too strong wind results in a switch off of the wind turbine. The result is a low efficiency, often reaching efficiency degrees of only 20% or even less.

The composition of the German electricity generation facilities has experienced significant changes over the last years. In particular the turn of the millennium marks a turning point in the German energy policy. At this time, the German government passed the Renewable Energy Act, the Erneuerbare-Energien-Gesetz (EEG). The intention of the law was to increase the share of renewable energy in the Ger-

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[176]Cf. Ockenfels et al. (2008), p. 15.

man generation mix. The EEG defines fixed and guaranteed prices for electricity generated by generation technologies based on renewable energies. The result is a significantly improved risk structure for investments in these generation technologies. Thus the act provides incentives for the construction of renewable energy generation capacity. The investment process in renewable energies is stimulated. Finally, the share of renewable energies on the German electricity generation significantly increased.[177] The quantitative aim of the act is an increase of the share of renewable energies on the total electricity generation to at least 30% in 2020 and a further continuous increase afterwards.[178] However, the economic impact of the implemented system is under controversial discussion.[179]

The results of this decision can be already seen in the evolution of the generation mix over the last years. Starting with 1.1% in 1990, the combined share of the renewable energies increased from 2.1% in 1999 up to 6.8% in 2008.[180]

Traditionally, a high concentration is observed in the ownership of the German generation capacity. At the moment the German market is characterized by the existence of four large utilities who control almost 80% of the total generation capacity. The four utilities are E.On (34%), RWE (27%), Vattenfall (11%), and EnBw (7%).[181] The German regulator, the Federal Network Agency, assumes that RWE and E.On, with a combined market share of over 60%, form an oligopoly in the German generation market.[182]

2.2.3.4 Retail Electricity Price

Regarding the retail electricity price, two different prices need to be distinguished. The first is the electricity price charged from household customers, the second is the electricity price charged from industry consumers.[183] The reason for the differentiation are the differences in the demanded amount, the demand profile, and the distribution channels.

Figure 2.9 depicts the evolution of the two price time series between 1991 and 2007. The straight line is the household price, the dashed line the industry price.

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[177]Cf. Wawer (2007), pp. 97-101.

[178]Cf. Erneuerbare-Energien-Gesetz (2008).

[179]Cf. for example Frondel et al. (2010).

[180]With the political decision to step off from nuclear technology the future development of the electricity generation based on renewable energy becomes even more critical for the German electricity supply

[181]The statistic is based on all power plants with a nominal capacity larger than 100 MW.

[182]Cf. for example Bunn & Karakatsani (2008).

[183]In general, a classification by the annual consumption is undertaken. According to Eurostat (2009) household consumers are defined as the consumer band between 2,500 and 5,000 kWh and industry customer as the consumer band between 500 and 2,000 MWh.

Figure 2.9
Evolution of German End Consumer Electricity Price 1991-2007
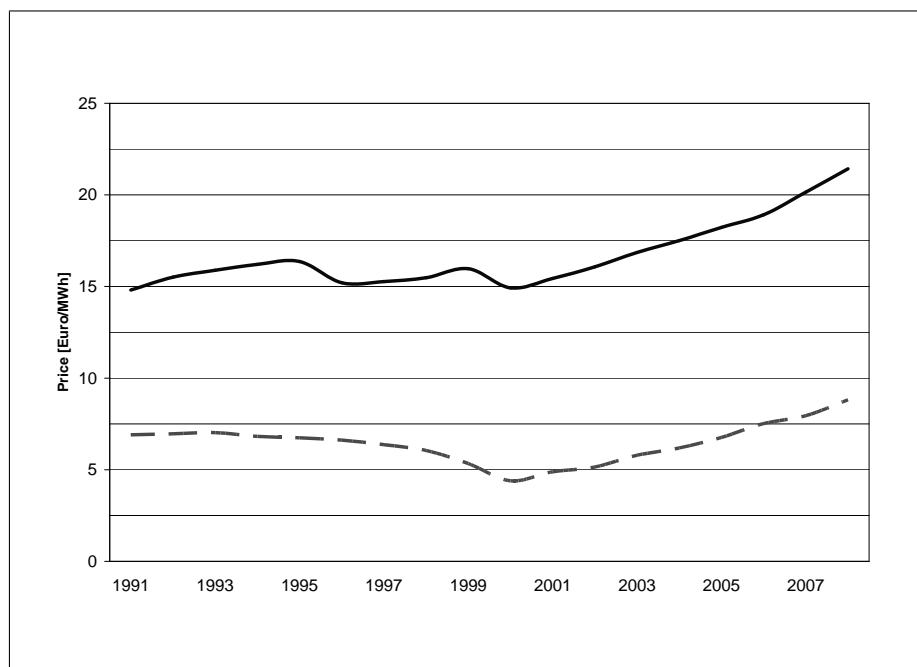
Source: Own work, based on data from Bundesministerium für Wirtschaft und Technologie (2010).

The price evolution in figure 2.9 reveals that beginning with the liberalization in the mid of the 1990s the electricity price started to decline. However, the phase of declining prices preserved only for a few years and, after reaching a minimum in 2000, a phase of increasing prices followed. This phase has continued until now; the introduction of the emissions right trading in 2005 had no visible impact on this trend. Thus it seems to be legitimate to pose the question whether the hoped lowering of electricity prices was not reached by the liberalization.

To answer this question a closer look at the underlying price components of the consumer price has to be taken. To gain an understanding of the price components the decomposition of the German private end consumer price in 2007 is used. This year's consumer price is affected by seven price components. In decreasing importance these are (the percentage of the cost factor on the private end consumer price is found in the brackets):

- electricity generation (37%),

- transmission (24%),

- sales tax (16%),

- electricity tax (9%),

- license fees (8%),

- EEG[184] (5%), and

- KWK[185] (1%).

Regarding to this statistic it is rather difficult to answer the question on the impact of the market liberalization on the prices. This is due to both the relatively low share of the electricity generation on the total end price and the introduction of new price components by the EEG in recent years. Thus, the literature on this topic is very mixed and the final answer to this question is still outstanding.[186]

A comparison of the German electricity price with the prices in other European countries reveals that the German prices are above the average price. According to the available statistics Denmark has the highest household prices (0.299 Euro/kWh) and Italy the highest industrial prices (0.1435 Euro/kWh). The average household price in Europe is 0.1659 Euro/kWh, the average industrial price 0.0987 Euro/kWh. The prices reported for Germany are 0.2528 Euro/kWh, and 0.1132 Euro/kWh, respectively. The data are based on prices for 2009 and include all taxes. However, it has to be noted that the above discussion showed that the comparison does not enable to draw conclusions on the total generation costs. The non-generation costs in Germany are higher than the generation costs; the same could be observed in other countries.

2.2.4 European Energy Exchange

2.2.4.1 General Remarks

The German marketplace for electricity is the EEX.[187] The EEX is an electronic exchange which was established in 2002 as a result of a merger between the Leipzig Power Exchange (LPX) and the former European Energy Exchange, previously based in Frankfurt am Main.[188]

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[184]Erneuerbare-Energien-Gesetz; allocation of cash flows to finance the guaranteed prices – which are significantly higher than the market price – for electricity that is generated based on renewable energies.

[185]Kraft-Wärme-Kopplung; surcharges for combined heat and power plants.

[186]Cf. for example Bonneville & Rialhe (2005) for a discussion of the impact of liberalization.

[187]Cf. Soennecken & Pilgram (2002) for a discussion of the newly founded EEX in 2002.

[188]The LPX was founded in 1999, the EEX in 2000. The focus of the LPX was on the trading of hour contracts in the day-ahead market; the focus of the EEX was on the trading of block contracts in a continuous (block) market.

The EEX is based in Leipzig and operated by the EEX AG.[189] The EEX sees itself as an European marketplace. It pursues the strategy of an open business model[190] to generate more flexibility, market coverage, and liquidity. This is achieved through targeted spin-offs and co-operations.[191] Being a public sector institution the EEX is subject to the German exchange law. Also being a derivatives trading place the German Securities Trading Act, the Wertpapierhandelsgesetz (WpHG), applies for the derivatives market. Furthermore the EEX is monitored by the German Federal Financial Supervisory Authority, the Bundesanstalt für Finanzdienstleistungsaufsicht (BaFin).

The tradable commodities on the EEX are coal, electricity, emission rights[192], and gas[193]. Emissions rights, electricity, and gas contracts are traded both in a spot and in a futures market. Coal is only traded in the form of financial futures. Clearing[194] of OTC trades in electricity is also offered by the EEX.[195]

In the following I solely focus on the electricity segment of the EEX.

The EEX is the largest electricity exchange in continental Europe and – after the Scandinavian Nord Pool – the second largest in Europe. As of the end of 2009, 191 market participants from 19 countries trade in the spot and futures market of the EEX.[196] The total traded volume in the spot market in 2009 was approximately 203 TWh, in the futures and forward market[197] around 1025 TWh.[198] Compared with the above reported statistics for the German electricity market these numbers translate to a factor of two between the traded and the consumed electricity in the German market. When compared with the yearly (gross) electricity consumption of around 600 TWh almost 25% of German electricity is traded in the physically settled spot market of the EEX.

In 2008, the EEX and the French energy exchange Powernext declared an intense cooperation regarding their electricity trading activities. The results of this cooper-

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[189]The EEX AG is a public company which has two large shareholders, the Eurex (European Exchange) Zürich AG with 34.73% and the Landesbank Baden-Württemberg with 22.64%. The remaining shareholders mainly include utilities, energy trading companies, and banks.

[190]The preamble of the EEX exchange rules states that "the EEX and its holding companies see themselves as a European market place and aim to develop this market place, e.g. by means of co-operations"; EEX (2010*a*), p. 4.

[191]Cf. EEX (2010*b*), p. 1.

[192]The trading of emission rights was introduced in 2005 when the European Union Emission Trading System (EU ETS) was launched.

[193]The trading of gas contracts was introduced in 2007.

[194]Cf. Soennecken et al. (2002) for a discussion of the OTC clearing on the EEX.

[195]In 2006 the EEX AG founded the European Commodity Clearing AG (ECC) as a 100% subsidiary. The ECC now serves as the central counterparty in all trades.

[196]Cf. section 2.2.4.4 for a discussion of the market participants on the EEX.

[197]Only forwards cleared by the EEX are included in this statistic. It is estimated that the OTC forward market is multiple magnitudes larger than the exchange trading.

[198]Cf. section 4.4.1 for a discussion of the liquidity on the EEX.

ation are a joint electricity spot market and a joint electricity futures market. The spot market – operated by a Societas Europaea, the EPEX Spot SE, of which both parties held 50% – is now located in Paris.[199] The futures market – organized in the EEX Power Derivatives GmbH[200], majorly owned by the EEX – is located in Leipzig.

2.2.4.2 Market Structure and Traded Products

The electricity segment of the EEX consists of a spot[201] and of a derivatives market[202]. The spot market is comprised of two market segments, an intraday and a day-ahead market. This is a market structure which can be found in most electricity exchanges. The day-ahead market has been active since the founding of the EEX. The intraday market was introduced in September 2006. In addition, contracts for three specific blocks of hours have been traded in a block contract market until August 2008. The derivatives market consists of a futures and of an options market.

Figure 2.10 summarizes the market structure of the electricity segment of the EEX. I discuss the individual market segments, and the traded products in this market segments, in the following separately. The focus is here on contracts with delivery, or rather settlement, in the German market area.[203]

Day-Ahead Market

Contracts with a delivery period of one hour are traded in the day-ahead market. These hour contracts[204] ensure the delivery of electricity for a specified delivery hour. The contract size[205] is 0.1 MW and the settlement of the contracts is physical.[206]

The price finding mechanism in the day-ahead market is a uniform auction, a common and accepted mechanism in electricity day-ahead markets.[207] In each auction 24

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[199]Now electricity for physical delivery in four countries – Germany, France, Austria, and Switzerland – is traded on the spot market of the EEX.

[200]The derivatives market was spun off to the EEX Power Derivatives GmbH in September 2008. The foundation of the new subsidiary was conducted respectively as of January 1, 2008.

[201]The trading in the spot market is based on the XETRA (Exchange Electronic Trading), the electronic securities trading system of the German stock exchange operator, Deutsche Börse AG.

[202]The trading in the derivatives market is based on the electronic system of the derivatives exchange EUREX, jointly operated and owned by the Deutsche Börse AG and the Swiss exchange operator SIX Swiss exchange.

[203]The other market areas serviced by the EEX are Austria, France, and Switzerland.

[204]Cf. EEX (2008*b*) and EEX (2008*a*) for further details regarding the contract specifications.

[205]Load profile is another term used for the contract size. Contract size refers to the delivery rate, i.e. the quantity of electricity per hour. Based on the contract size the contract volume is determined as the product of delivery rate and the number of delivery hours in the delivery period.

[206]The delivery of the electricity can take place in one of the following control areas: Amprion GmbH, Transpower Stromübertragungs Gmbh, 50Hertz Transmission GmbH, EnBW Transportnetze, and Austrian Power Grid.

[207]Cf. Ockenfels et al. (2008) for an academic review of the trading process in the day-ahead

Figure 2.10
Market Structure EEX
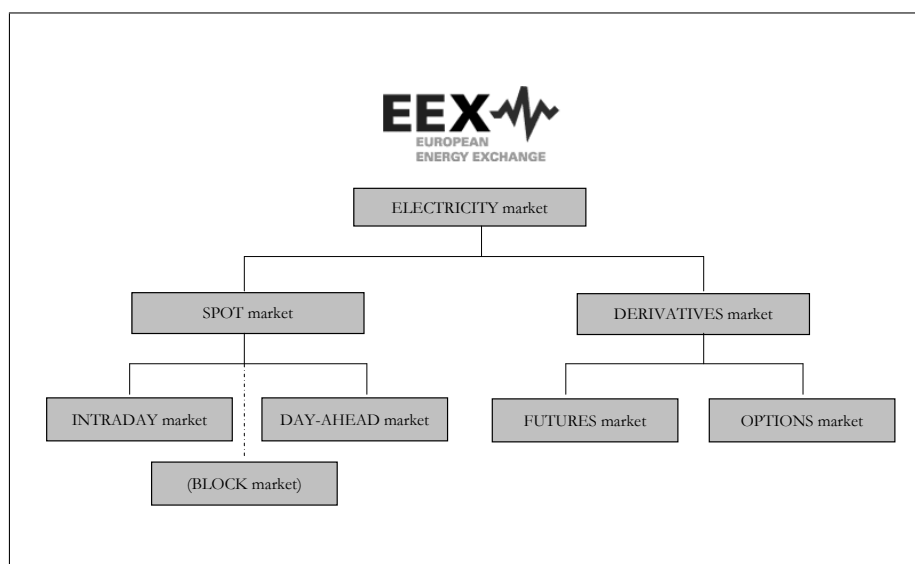
Source: Own work.

independent prices are established for each hour of the delivery day. Until September 2008, auctions were only taking place from Monday to Friday excluding public holidays. On Fridays and before public holidays more than one auction accordingly took place. Starting September 9, 2008 the EEX introduced seven-day-trading in the day-ahead market.

The predefined price range in the day-ahead market is from minus 3,000 up to 3,000 Euro/MWh. The possibility to bid negative prices[208] in the day-ahead market was introduced in September 2008. The minimal price fluctuation is 0.1 Euro/MWh.

In addition to the hour contracts block contracts can be traded in the day-ahead market. Besides the standardized blocks[209] market participants can define arbitrary combinations of hours. Block bids are a special bid form that ensures that either all or none of the specific hour contracts are traded, resulting in an 'all-or-nothing' bid.

The EEX calculates a daily and a monthly index for the day-ahead market, the Physical Electricity Index (Phelix). The daily index is calculated as a simple arithmetic average of the hourly prices for the base (0 am to 24 am) and peak hours (8 am to 8

market.
[208]Cf. section 2.2.2.2 for a discussion of negative prices in electricity markets.
[209]The standardized block orders are: block baseload (hour 1 to 24), block peakload (hour 9 to 20), block night (hour 1 to 6), block morning (hour 7 to 10), block high noon (hour 11 to 14), block afternoon (hour 15 to 18), block evening (hour 19 to 24), block rush hour (hour 17 to 20), block off-peak I (hour 1 to 8), block off-peak II (hour 21 to 24), and block business (hour 9 to 16).

pm), resulting in the daily Phelix Base and Phelix Peak.[210] In addition, a monthly index is calculated as an arithmetic average of the daily index values. The monthly Phelix Peak is calculated only based on prices between Mondays and Fridays; non-working days are ignored. The daily Phelix Base can be seen as the reference price in the German electricity market.

Intraday Market

In the intraday market hour contracts with similar specifications as in the day-ahead market are traded. The intraday hour contracts have a contract size of 0.1 MW and the minimal price fluctuation is 0.01 Euro/MWh.

The permitted price range for intraday market contracts is from minus 9,999 up to 9,999 Euro/MWh. Negative prices in the intraday market were introduced in December 2007. Similar to the day-ahead market trading at negative prices occurs occasionally.[211] In contrast to the day-ahead market the intraday market is operated as a continuous market with trading taking place around the clock.

Block Contract Market

Trading took place in the block contract market until August 2008. Block contracts ensured the delivery of power over several delivery hours with a delivery rate of 1 MW. Traded block contracts were a base load, a peak load, and a weekend base load contract.[212] The base load block contract ensured the delivery of electricity throughout the day while the peak load block contract only ensured the delivery in the peak hours (8 am to 8 pm). The base load block contract was available for all days, the peak load block contract only between Mondays and Fridays. The weekend base load block contract ensured delivery in all hours of the weekend.

A price range was not specified in the block contract market. Only a positive price was required, translating to a minimum price of 0.01 Euro/MWh. The minimum price fluctuation was 0.01 Euro/MWh.

Today, the same blocks of (delivery) hours as in the block contract market can be traded by bidding for the specific hours in the day-ahead market. The orders for these synthetic blocks can be made in the form of a block bid already discussed above. However, the block bids do not have a pricing of their own as block contracts in the block contract market had.

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[210]Cf. section 4.4.2.1 for a discussion of the daily seasonality in electricity markets.

[211]See section 4.4.2.1 for a discussion of negative prices in the day-ahead and intraday market.

[212]The weekend base load block contract was introduced at a later date compared to the two other block contracts, starting trading on November 1, 2002. However, replicating the weekend base load block contract had already been possible by taking long positions in base load contracts with delivery on a Saturday and on a Sunday.

Futures Market

Together with the options market the futures market forms the derivatives market of the EEX. Four kinds of futures are traded on the futures market which are characterized by their delivery period, e.g. one week, one month, one quarter, and one year. The week futures were introduced recently, while the other three futures are traded from the beginning.

The minimum price fluctuation in the futures market is 0.01 Euro/MWh. Negative prices are not allowed and a maximum price is not specified. The contract size of the futures is 1 MW.

The settlement of the traded futures can take place either in cash – these are the so called Phelix-Futures – or through physical – these are the so called German-Power-Futures – delivery.[213] The week future is only traded with financial settlement. The overwhelming part of the liquidity in the futures market is observed in the cash-settled futures. The liquidity in the separate market segments will be further discussed in section 4.4.1.

There is a base and a peak load version of every future. A base contract ensures delivery around the clock, independent of working or non-working days. A peak contract ensures delivery between 8 am and 8 pm and between Mondays and Fridays, independent of non-working days. A month future, for example, ensures the delivery of electricity in all hours of any delivery day of a calendar month (base version) or on all delivery days from Monday until Friday from 8 am to 8 pm (peak version). The Phelix Base and the Phelix Peak are the underlying for the cash-settled base and peak futures, respectively. Recently, the product range was extended through the introduction of an off-peak future. The off-peak future is only offered as a future with financial settlement, i.e. as a Phelix Off-Peak future. This future is settled in between midnight and 8 am and between 8 pm and midnight, from Monday to Friday and around the clock for Saturday and Sunday.

Currently traded delivery periods are the actual week and month, the next four weeks, the next nine months, the next eleven quarters, and the next six years.[214] A special feature of the futures market is the cascading of the quarter and year futures. In the case of quarter futures the original future is replaced by three month futures – together representing the delivery quarter – before the delivery period. The year future is replaced by three quarter and three month futures. Another interesting aspect of the futures market is the trading of the month futures in the delivery

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[213]The futures with physical delivery in France are called French Power Futures. There are no financially settled French futures.

[214]As already discussed above, the number of traded contracts continuously increases as the EEX extends its product portfolio.

month.[215]

Options Market

Options called Phelix options are traded in the options markets of the EEX. The Phelix options are European styled options on the Phelix Base future, i.e. the exercise of these options opens a position in the underlying future. Both puts and calls are traded. Every option is characterized by the underlying future, the exercise price, and the maturity. For every underlying future at least three options may be traded, i.e. at least three different exercise prices are available. The management board of the EEX may also establish additional option series.

Traded options are available on the respective next five Phelix Base month futures, the respective next six Phelix Base quarter futures and the respective next three Phelix Base year futures. The minimum price fluctuation in the options market is 0.001 Euro/MWh. Negative prices are not allowed and an upper price limit does not exist.

The exercise of an option that is in-the-money takes place on the last trading day. The exercise of the option opens a position in the underlying future at the exercise price of the option.

2.2.4.3 Trading Process

Similar to the previous section I separately discuss the trading process in the various electricity market segments in the following.

Day-Ahead Market

The day-ahead market is operated as an auction market. Thus, all buy and sale orders are collected in an order book before the auction takes place. For a specific hour contract orders can be entered, changed, deleted, or retrieved up to 14 days before delivery. The order book remains the whole time closed, i.e. it is not possible for the market participants to see the already entered orders. The auction takes place on the last day before the delivery day of the hour contract.[216]

Figure 2.11 depicts the detailed trading process on the auction day with a further specification of the four trading phases distinguished by the EEX for this day. These phases are the pre trading, the main trading, the post trading, and the batch processing phase.

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[215]Cf. section 4.4.1.2 for a discussion of the trading of the month futures in the delivery month.
[216]Cf. EEX (2008*b*) for further details regarding the trading process.

Figure 2.11
Trading Phases Day-Ahead Market EEX
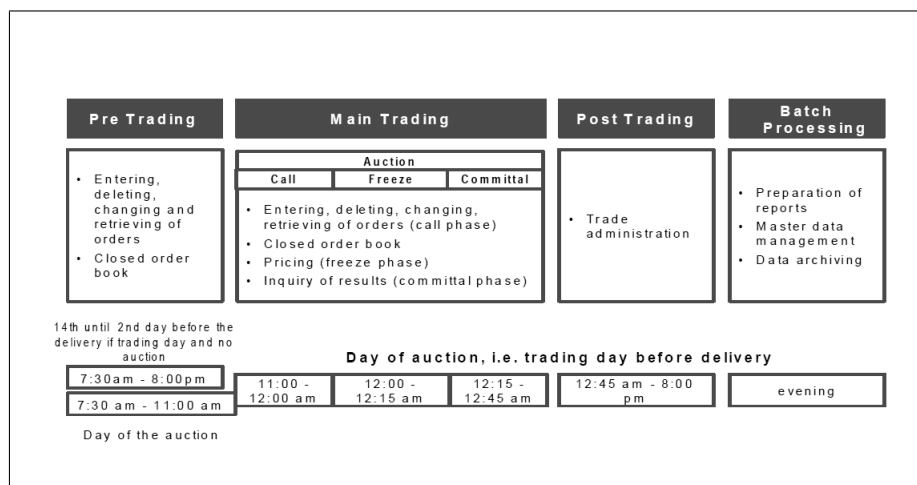
Source: Taken from EEX (2008*b*), p. 13.

The market participants – both electricity seller and buyer – have two possibilities to enter hourly bids: the price-dependent and the price-independent bid. The price-dependent bid consists of the specification of various price-volume combinations. The minimum and maximum prices are predetermined by the allowed price range. At least two price-volume combinations at the minimum and at the maximum price must be specified. Up to 248 more price-volume combinations can be entered. These are then interpolated to a bidding curve. The price-dependent bid is hence a bid with continuous price quotations between the minimum and the maximum price.[217] These bid curves specify which volume a market participant is willing to buy or to sell at a certain price. It is common for a market participant to act both as a buyer and as a seller in the same hour contract in dependence of the price.[218] A price-independent bid on the other side only consists in the specification of a volume that is to sell or to buy. The bid is executed independent of the price.

The prices for all hour contracts are established in a joint auction. For contracts with delivery in the German and Austrian market area the auction starts at 12 am. In the auction all hourly bids are aggregated to form a supply and a demand curve. An iteration process taking into account various restrictions establishes the prices for the 24 hour contracts.[219] One price is established for every hour contract; every market participant pays or receives the same price. The auction is hence called a

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[217]Cf. EEX (2008*b*), p. 17.
[218]Cf. section 2.2.4.4 for a discussion of the market participants and their bidding behavior.
[219]Cf. EEX (2008*b*) for a further discussion.

uniform price auction in contrast to a pay-as-bid auction.[220] The auction results – the established price and the traded volume for every hour contract – are published by the EEX between 12.35 pm and 12.45 pm.

Another characteristic of the trading process in the day-ahead market is the fact that besides the volume to sell or to buy at a certain price the market participants also need to specify the control area in which the electricity delivery will take place or rather is desired.[221] In the case of a system congestion between two or more control areas different prices for the same delivery hour in dependence of the control area can be established. However, until now congestion did not occur in the German market.

To provide the market participants with further information regarding the auction results, the EEX publishes the aggregated supply and demand curves of every hourly auction on the next exchange day at 9 am. Market participants hence have the time to process the provided information and to adjust their bidding behavior for the current day.

Intraday Market

The intraday market is operated as a continuous market where matching orders are executed automatically. Trading in a specific hour contract starts at 3 pm of the previous day and lasts up to 75 minutes before the beginning of the delivery hour. The length of the trading period of the hour contract for a certain delivery day is different since every contract has the same starting point of trading but a different ending point.

The trading in the intraday market takes place around the clock, seven days a week. The price formation is based on the immediate execution of matching orders.

Block Contract Market

The trading in the block contract market included an auction mechanism as well as a continuous trading period. The trading window in this market segment was between 8 am and 12 am.

The trading process in the block contract market on the trading day consisted in accordance to the day-ahead market of four phases: The pre-trading, the main-trading, the post trading, and the batch-processing. During the pre-trading – lasting from 7.30 am to 8 am – market participants could enter, change, delete, and retrieve orders. The order book remained closed during that trading phase. At the beginning

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[220]Cf. Ockenfels et al. (2008) for a discussion of the two auction forms.

[221]From a physical point of view it is not possible to transmit electricity to a certain point. Thus, the place of delivery is a specified area.

of the main-trading phase these orders were then used for the opening auction.[222] Afterwards, a continuous trading period followed. At the end of this period again an auction, the closing auction took place. The orders for the closing auction could be entered within a five minute timeframe. The post trading and batch-processing phases served the administration of the trades, the compilation of reports and the storage of the accrued data.

Futures Market

The futures market is operated as a continuous market. Trading takes place on exchange days between 8.25 am and 4 pm. The clearing of OTC trades starts at 8.25 am and ends at 5.30 pm.

The last trading day of the year and of the quarter futures is three exchange days before the commencement of the delivery period. The month futures are traded for the last time on the day before the last delivery day (Phelix futures) or two days before the last delivery day. This implies that the month futures are traded during their delivery month. A special feature of the pricing mechanism in the futures market is the establishment of daily prices for every tradable future contract.[223] This means that even on days when no trading in a certain contract takes place a price for this future contract is established.[224]

In this case the price finding mechanism is either based on the order book situation or on the so-called chief trader procedure.[225] Within the chief trader procedure every market participant is asked by the EEX for a price indication for the non-traded contracts. The settlement price is then calculated by the EEX as a simple average price under consideration of certain constraints.

One of the constraints is an existing arbitrage relation between futures with different delivery periods. To clarify the arbitrage relation a closer look at the quarter future with delivery in the second quarter of 2009 is taken. For this quarter, five simultaneously traded futures with delivery taking place in this quarter exist: the year future with delivery in 2009, the quarter future with delivery in the specific quarter, and the three month futures with delivery in April, May, and June 2009.

For the price of the quarter future with delivery in the second quarter in 2009, P_Q,

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[222]According to Ronn & Wimschulte (2009) almost all trading in the block contract market took place in the continuous trading period.

[223]This is done "for the purpose of the execution of all clearing processes, in particular for the calculation of the variation margin for every trading participant"; EEX (2008*b*), p. 50.

[224]Cf. section 4.4.1.2 for a discussion of the liquidity in the futures market.

[225]Cf. EEX (2008*b*), pp. 51-52.

the following relation applies

$$P_Q = \frac{1}{n}(n_1 P_{M1} + n_2 P_{M2} + n_3 P_{M3}). \tag{2.10}$$

P_{M1} is here the price of the month future with delivery in the first month of the delivery quarter, namely the month future with delivery in April 2009. P_{M2} and P_{M3} are the prices of the month futures with delivery in May 2009 and June 2009, respectively. n_1 is the number of delivery days in April 2009, n_2 and n_3 the numbers of delivery days in May and June 2010, respectively. n is calculated as the sum of n_1, n_2, and n_3. The arbitrage relation arises from the fact that a long position in these three month futures would be equivalent to a long position in the quarter future. Traders can earn a risk-less profit when the condition stated in equation (2.10) is not fulfilled.[226]

The above equation links the price of the quarter futures to the prices of the month futures. Thus, if no trading in the quarter futures takes place, the arbitrage-free price of this future can be calculated with equation (2.10). Needless to say, in this case trading in the corresponding month futures must take place to establish a reliable price. Similar arbitrage relation applies to the other futures. A long position in a year future, for example, can be replicated by long positions in the corresponding three month futures and the corresponding three quarter futures. Thus, the price of the quarter futures discussed above can also be linked to the year future and the other quarter futures of the corresponding delivery year by an arbitrage relation.

Options Market

The trading hours in the options market are identical to those in the futures market. The options market is also operated as a continuous market.

The last trading days of the option are: Four days before the beginning of the delivery period for the Phelix month and quarter options, the second Thursday in December for the Phelix year option. For options with the delivery period being the first quarter of a year and January, the last trading takes place on the third Thursday in December of the previous year. Similar to the futures market prices for all options are established every day. Non-traded options are valued by an options pricing model.[227]

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[226]Cf. Wimschulte (2010) for a discussion of a similar short-term condition in the Nord Pool and empirical evidence that the condition is fulfilled, i.e. that the market is efficient.

[227]Cf. EEX (2008*b*), p. 52.

Figure 2.12
Market Participants EEX by Number and Country of Origin in 2009
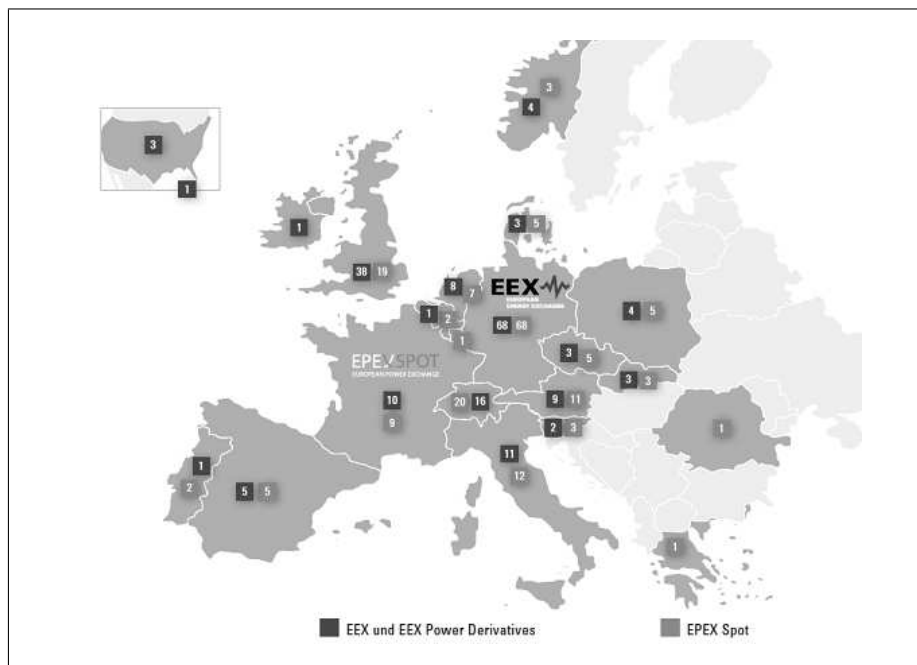
Source: Taken from EEX (2010*b*), p. 1.

2.2.4.4 Market Participants

As of December 31, 2009 the number of the market participants amounted to 191 in the derivatives market and to 182 in the spot market. Regarding their countries of origin the distribution of the market participants is found in figure 2.12. The figure reveals that after Germany the main countries of origin are Great Britain, Switzerland, Austria, and France.

Market participants on the supply side are mainly utilities, industrial companies with generation capacities, and foreign electricity importers. On the demand side mainly industrial companies, supply companies as municipal energy suppliers, trading companies, the trading division of the utilities, banks and other financial institutions are found.

However, the classification of a market participant to be either a (pure) supplier or buyer is often not possible. As prior discussed in this section, regarding the trading process in the day-ahead market, market participants enter hourly bids which place them on different market sides in dependence of the price. Thus, it is to observe that market participants regularly change the market side. For a utility with a peak load power plant, for example, the buying of electricity at the spot market

instead of operating its own power plant can be reasonable at certain prices. Thus, a classification based on the net positions of the market participants in certain trading intervals is the best classification available mechanism .

The EEX tries to enhance transparency by publishing additional information regarding the trading participation. Considering the day-ahead market the following data are published on a daily basis:[228]

- Number of active market participants,

- Number of sellers,

- Number of buyers ,

- Number of net-sellers,

- Number of net-buyers, and

- Average share of the five market participants with the highest revenue (per market participants).

The data publication for a certain delivery day takes place on the homepage of the EEX at 9 am the same day.

In addition, the following data considering the trading in the futures market are published on the first exchange day of a calendar month:[229]

- Average share of the five market participants with the highest revenue (per market participants) in the Phelix month futures,

- Average share of the five market participants with the highest revenue (per market participants) in the Phelix month futures including the OTC market, and

- Share of the market makers on the total revenue in the derivatives market.

According to the EEX the number of net-sellers in 2008 was on average higher than 40, more than half of these sellers not being from Germany.[230]

A further measure to increase market transparency is the publication of generation and consumption data on a neutral transparency platform.[231] Around 80% of the German capacity is covered by this platform.

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[228]Cf. EEX (2009*a*), pp. 64-65.

[229]Cf. EEX (2009*a*), p. 65.

[230]Cf. EEX (2009*a*), p. 59.

[231]Cf. the website of the transparency platform (www.transparency.eex.com) for a discussion of the provided data.

Figure 2.13
Evolution of German Wholesale Electricity Price 2002-2010
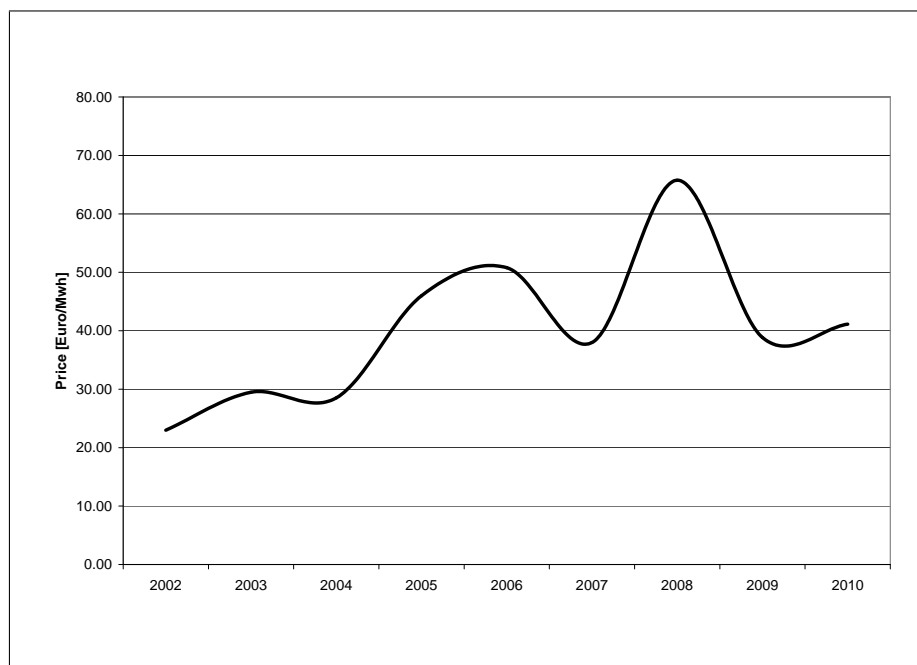
Source: Own work, based on data from EEX.

2.2.4.5 Wholesale Electricity Price

The average (daily) hourly wholesale electricity price in the German day-ahead market amounted to (38.89) 38.86 Euro/MWh in 2009. In 2003, the first full year of existence of the EEX, the average price was (29.73) 29.49 Euro/MWh. This price evolution would correspond to a price increase of approximately (31) 32% over six years. However, a near analysis of the time series reveals that over the first six years a gradually price increase took place. The time series is shown in figure 2.13. It can be seen that in 2008 a price peak was reached. The average price in 2008 amounted to 66.14 Euro/MWh. In addition, a large price increase is observed in 2005. Overall, an increasing trend is observed over the first years. This trend in the price evolution was stopped by the recent financial and economic crisis which caused a strong price decline in 2009.

A continuously increasing electricity price over the whole lifespan of the EEX seems to be a characteristic of the liberalized German electricity market. The literature mainly identifies two fundamental drivers of this development: the increasing fuel costs, in particular the anthracite price and gas price, and the introduction of the emission rights trading in 2005.[232]

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[232]Cf. for example Schwarz et al. (2007) and Bundesministerium für Wirtschaft und Technologie

In particular the introduction of the European Union Emission Trading System (EU ETS) has marked a significant change for the established market structures since the liberalization. A completely new cost block was introduced through this change, namely the exchange traded emission right or, officially, the emission allowance unit (EAU).[233] The EAU grants the right to emit one tonne carbon dioxide (CO_2) or an equivalent in the European Union. At the beginning of the trading in 2005 the EAUs were allocated for free; a gradual increase of the sold emissions is intended over the years. However, opportunity cost considerations resulted already in the first year of the EU ETS in an sharp increase of the wholesale electricity price as the electricity generation side incorporated the emission right's price (at least partially) into the electricity price. The results were high windfall profits for the power sector[234]. Since then, the electricity price development is directly linked to the emission rights price development.[235] However, Zachmann & von Hirschhausen (2008) show in an early work that the price changes in the emission rights market are passed asymmetric into the electricity prices. According to the results of the authors positive price changes of emission rights have a stronger impact on the wholesale electricity price than falling prices.

In addition, parts of the academic literature show that besides these factors market power influences (or influenced in past periods) the electricity prices as well[236]. Market power is, in general, defined as the ability (of market participants) to profitably alter prices away from competitive levels (fair market prices); market power is widely discussed in the literature. The discussion on the existence of market power in the German electricity market and on measures to migrate it is almost as old as the EEX.[237] The methodology applied in academic studies consists almost always in the ex post comparison of observed and modeled electricity prices and is very sensitive to the underlying assumptions regarding the modeling of the theoretical prices.[238] Unsurprisingly a reasonable number of studies finds mixed or even contrary results.[239]

(2009).

[233] The EU ETS implements a cap-and-trade mechanism with an absolute (emission) cap within the European Union; cf. for example Benz & Trück (2006), Convery & Redmond (2007), Ellerman & Buchner (2007), Kruger et al. (2007), Daskalakis & Markellos (2008), and Daskalakis et al. (2009) for details regarding the emissions trading in the European Union and the implemented trading mechanism.

[234] Cf. for example Frondel et al. (2008).

[235] Cf. for example Sijm et al. (2006) for a discussion of the interdependence between the emissions rights price and the electricity price.

[236] Cf. for example Müsgens (2006), von Hirschhausen et al. (2007), Weigt & von Hirschhausen (2008), and Janssen & Wobben (2009).

[237] Cf. Schwarz & Lang (2006) for one of the first empirical studies on market power in the German wholesale market.

[238] Cf. Ellersdorfer et al. (2008) for a discussion of potential problems when modeling theoretical prices.

[239] Cf. for example Schwarz et al. (2007) and Möst & Genoese (2009)

The results for other markets are mixed as well.[240] Further problems complicate the detection of market power even more.[241]

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[240]Cf. Fridolfsson & Tangera (2009) for a discussion of market power in the Nord Pool.
[241]Cf. Bautista et al. (2007) for a discussion of these problems.

2.3 Price Formation in Commodity and Electricity Futures Markets

The research on price formation in commodity futures markets dates back to the work of Keynes and his theory of backwardation. Two theories have been established since then in the academic literature: the theory of storage and the risk premia approach. As the empirical literature finds support for both theories an understanding of the similarities and differences between these two theories is necessary in order to evaluate their suitability in the case of electricity markets.

In this section I summarize the theoretical and empirical research on price formation in commodity futures markets. Thereby, I focus on commodity futures markets, as the main characteristic that is of interest in the case of electricity is storability. After an introduction to the topic I provide an overview on the theory of storage and the risk premia approach. I discuss the theoretical background of these theories and then address the specifics of electricity futures markets, in particular the non-storability from an economic point of view and the resulting futures character of all exchange-traded electricity contracts. Afterwards, I report the empirical evidence on price formation in commodity futures markets over the last three decades. Furthermore, I devote considerable attention to a literature review on the empirical research on electricity futures markets. Thereby, I distinguish between theoretical results, empirical results on short-term contracts, and empirical results on long-term contracts. Short-term contracts are generally defined as day-ahead contracts, while long-term risk contracts are defined as week and month futures. I summarize the obtained results according to magnitude and the sign of risk premia. Moreover, I address time variation, seasonality and their potential drivers.

This section aims to answer the following three key questions:

- Which are the standard theories for price formation in commodity futures markets?

- Which of these price formation theories is appropriate for electricity futures markets?

- What is the empirical evidence on price formation in electricity futures markets?

2.3.1 Introductory Remarks

Shortly after the beginning of the worldwide deregulation of electricity markets and the establishment of electricity exchanges as wholesale markets, the question on the theoretical foundation of price formation in electricity (futures) markets was posed. In contrast to financial and other commodities markets, where the theory of storage as a non-arbitrage condition can be mostly applied, electricity is non-storable. As storability is the basic assumption of the theory of storage, this mechanism is not applicable[242] in the case of electricity futures.[243] Thus, the question about the mechanism behind price formation in electricity futures markets has accounted for immense research over recent years.

From an equilibrium point of view, the risk premia approach seems to be the most promising price formation mechanism. In general, this approach identifies two possible determinants of risk premia: systematic risk and hedging pressure (Bessembinder (1992)). The existence of the first determinant, systematic risk, is under controversial discussion. The main part of the empirical literature finds no evidence to support a systematic risk component in futures returns. The second determinant, hedging pressure, was introduced with the normal backwardation theory formulated by Keynes (1930) to the academic literature. Later, this theory was extended to the general hedging pressure theory, which indicates that the price formation of futures is based on two components, the expected spot price at maturity of the future and a risk premium. The risk premium is paid by risk-averse market participants as a compensation for the elimination of price risk.

There are currently mixed empirical results regarding the hedging pressure theory as an appropriate price formation mechanism in commodity markets.[244] Empirical literature suggests that this theory is appropriate for certain commodities, mostly characterized through no or rare storage possibilities. The work of Fama & French (1987) is one of the classic empirical studies on this topic.

Regarding price formation in electricity futures markets, the hedging pressure theory seems to be an appropriate approach.[245] However, the empirical results raise questions on the magnitude and sign of the risk premia. In the next chapter I focus on these questions for the German market.

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[242]Cf. Schwarz et al. (2007), pp. 58-59.

[243]However, Botterud et al. (2010) argue that in electricity markets with a high share of hydro power the theory of storage may also be relevant, as hydro power implies storability to a certain degree.

[244]Cf. section 2.3.3.1 for a discussion of the empirical results on commodity markets.

[245]Cf. section 2.3.3.2 for a discussion of the empirical results on electricity markets.

2.3.2 Price Formation in Commodity Futures Markets: Theory

2.3.2.1 Theoretical Approaches

Two standard theories are discussed in the academic literature as potential foundations for price formation in commodity futures markets[246]: the theory of storage and the risk premia approach.[247] The theory of storage links futures and spot prices through a no-arbitrage condition and relies on the storability of the underlying commodity.[248] The risk premia approach is a general equilibrium theory and links futures and spot prices through expectations regarding the future spot price and a risk premium. Two potential determinants of the risk premium, namely systematic risk and hedging pressure, are identified. Therefore, the term *risk premia approach* is not well-defined.

Theory of Storage

The theory of storage, also known as cost-of-carry approach or hypothesis, is based on arbitrage considerations and relies on the assumption of storability of the underlying commodity. Kaldor (1939) and Working (1949) originated the theory. Later, Brennan (1958) and Telser (1958) refined and formulated the theory as it is known today.

Three factors, two of them fundamental in nature, form the backbone of the theory. The first fundamental factor is the interest that could be earned by the long position in a future on the fixed futures price. The second fundamental factor is the storage cost which occurs for the physical holding of the underlying asset. The third factor is generally called convenience yield and expresses the benefit from physically holding the asset.

In its analytic form the theory of storage expresses the futures price *F(t, T)* at time *t* with maturity in *T* as

$$F(t,T) = S(t)e^{r+u-y} \tag{2.11}$$

with *S(t)* as the spot price at time *t*, *r* the (risk-free) interest rate, *u* the storage cost, and *y* the convenience yield.

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[246]Regarding the pricing of financial futures, Copeland et al. (2005) state that "Financial instruments are usually traded in very liquid spot markets, and there is virtually no cost of storage. This distinguishes them from commodity markets where the spot market may be thin and storage costs high. It also makes financial futures somewhat easier to price because arbitrage between the spot and futures markets helps to determine the future price."; Copeland et al. (2005), p. 286.

[247]Cf. Chow et al. (2000) for a recent survey on price formation in futures markets.

[248]In the following I consequently use the term commodity. However, most of the argumentation is applicable to other assets as well.

The two fundamental factors in equation (2.1), the interest rate and the storage cost, are in reality always positive. The result is a futures price that is higher than the spot price. The convenience yield can be both positive and negative. Thus, depending on the market conditions this factor may lead to a higher or lower futures price compared to the spot price. The theory of storage can hence depict both a market in contango and a market in backwardation.[249]

The convenience yield is the crucial factor of the theory of storage as it is not directly observable. The convenience yield reflects the benefit of a physical holding of the commodity, i.e. the advantage of effectively possessing the commodity instead of having to rely on a (liquid) market. Kaldor (1939) states that "stocks of goods ... have a yield, qua stocks, by enabling the producer to lay hands on them the moment they are wanted and thus saving the cost and trouble of ordering frequent deliveries, or of waiting for deliveries".[250] The perception that the convenience yield is reciprocally proportional to the stocks of the underlying is the basic assumption in academic literature.

In an empirical verification of the theory of storage, the convenience yield is, in general, a residual factor. It is approximated as reciprocally proportional to the stocks of inventory. However, the approximation is still rough because of to two facts: first, the approximation by stocks of inventory itself is a strong simplification, and second, it is obviously difficult to estimate the worldwide stocks of an inventory. Similar to the implicit volatility in the Black-Scholes(-Merton) model, empirical research faces the problem that it can hardly falsify the model through an ex post analysis.

Risk Premia Approach

The risk premia approach identifies two potential determinants of risk premia: systematic risk and hedging pressure. In the following, I discuss both determinants individually.

Systematic Risk

The first step in valuating a financial instrument is, in general, the application of the CAPM. The intention is to determine a risk premium from the systematic risk in the returns of an asset. The earliest academic contributions on the valuation of commodity futures applying the CAPM are found in Dusak (1973) and Black (1976*a*).

Before a discussion on the valuation of commodity futures applying the CAPM can

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[249]A market in contango is characterized by futures prices being higher than the spot price; a market in backwardation is characterized by futures prices lower than the spot price.

[250]Kaldor (1939), pp. 3-4.

take place, a question which is essential for the application of this approach needs to be posed. The question is whether a commodity future may be treated as an asset, a necessary condition for applying the CAPM. Black (1976a) is of the opinion that commodity futures do not belong to the market portfolio. The author justifies this by stating that for every long position there is one short position – both thus neutralizing each other. This implies that commodity futures can be seen as perfect zero-sum games. In other words, according to Black (1976a), these futures contracts are mere bets on future prices of a good or a commodity. Dusak (1973), on the other side, argues contrarily, seeing futures markets as normal capital markets where trading takes place in the same way as with any other asset.

Following the argumentation that the valuation of futures based on the CAPM is appropriate, it is possible to calculate the futures price as the expected spot price adjusted for the expected risk premium.[251] In a one-period framework, it is possible to note the futures price as[252]

$$F(t,T) = E_t[S(T)] - [E(R_m - R_f)]S_t\beta. \tag{2.12}$$

The futures price $F(t, T)$ is equal to the expected spot price, $E_t[S(T)]$, minus a risk premium. This risk premium corresponds to the expected return from taking a long position in a future. The risk premium is defined as the sum of the risk-free interest rate, R_f, and of a component which is proportional to the systematic risk of the given future. The systematic risk, β, is defined as the covariance of the futures' returns with the returns of the market portfolio, R_m. It reflects the non-diversifiable share of the total risk. S_t is the spot price at time t.

As the covariance between the futures returns and the returns of the market portfolio can be either positive or negative, this approach can model both a market in contango or a market in backwardation.

Hedging Pressure

The hedging pressure theory arises from equilibrium considerations and dates back to Keynes (1930) and Hicks (1939).[253] Later that approach was generalized to the hedging pressure theory (Cootner (1960)). More recently, systematic risk and hedging pressure have been merged to joint models.[254]

Keynes (1930) assumes in his original work that producers always pay the risk pre-

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[251]Cf. Dusak (1973) for the derivation of the analytical relation and potential problems.

[252]Cf. Copeland et al. (2005), p. 291.

[253]John M. Keynes had formulated his idea on the normal backwardation for the first time already in an essay in the *Manchester Guardian Commercial* in 1923; cf. Keynes (1923).

[254]Cf. for example Stoll (1979), Hirshleifer (1988), and Hirshleifer (1989).

mium in order to get rid of their price risk.[255] From Keynes' perspective, in the words of Dusak (1973), "a futures market is an insurance scheme in which the speculators underwrite the risks of price fluctuation of the spot commodity".[256] Under the assumption that the expected spot price equals the current spot price, this results in a downward sloping term structure, i.e. a market in backwardation. Thus, Keynes' theory is termed the normal backwardation theory. The generalization was derived from the insight that consumers can pay the risk premium as well.

The hedging pressure theory is based on the expectation theory.[257] The hypothesis of the unbiased estimator is dropped and the existence of a risk premium postulated. The futures price is expressed as the sum of the expected spot price and a risk premium. Thus, in general, the futures price is a biased estimator of the spot price.

The hedging pressure theory assumes that futures markets consist of two general types of market participants: hedgers and speculators.[258] Market participants acting as hedgers are assumed to have a real interest in the underlying of the future. Their motivation, for example, is to ensure a smooth production process through hedging of the sales prices or actually delivering the commodity in the future. Market participants acting as speculators have only a financial interest.

Market participants seeking financial gains only enter a financial market if they can expect, on average, a positive return. Thus, speculating market participants need to be offered a positive expected return for taking of a position in the futures market. Thus, the offered bearing of the price risk must be compensated via a risk premium.

As hedgers may go short as well as long in the futures markets, it has become common to speak of producers and consumers. Normally, a producer possesses the commodity and takes a short position in a future in order to hedge the future price. On the other side, a consumer may have a need for the future's underlying and takes a long position in the specific future to secure the future price. Depending on the market structure, on the macroeconomic framework, and on various other factors, there may be a predominance of either producers or consumers acting as hedgers. Needing to hedge the future prices, consumers are willing to pay a premium for the counterparty's

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[255]The original theory of normal backwardation as formulated by Keynes (1930) is based on three main assumptions (Chatrath et al. (1997)): (1) market participants acting as speculators are risk averse (2) market participants acting as hedgers are net short, and (3) market participants acting as speculators do not have forecasting ability. The second assumption was released by Cootner (1960). The third assumption is discussed in more detail in section 4.3.

[256]Dusak (1973), p. 1387.

[257]In the financial literature the term *expectation theory* is generally used for a theory of the yield curve and forward interest rates. According to this theory, market participants' decisions on capital allocation are influenced by their expectations towards the future interest level. This implies that, according to the pure expectation hypothesis, futures interest rates and forward interest rates, may be interpreted as the unbiased estimators of future spot interest rates.

[258]Some authors see arbitragers as a further type of market participants; cf. for example Geman (2005).

willingness to take the counter position. The price risk as well as the corresponding risk premium are then transferred from the hedger to the counterparty in the future. The counterparty can be a hedger or a speculator. If there are as many producers as consumers neither of the parties needs to pay a risk premium; speculators are not required. Risk premia exist only if there is a predominance on one side (leading to the term hedging pressure), i.e. a net hedging pressure. Speculators are motivated to enter the market and take the counter position in the future in order to gain the risk premium.

The futures price *F(t, T)* at time t with maturity in T is defined by the risk premia approach in a formal way as

$$F(t,T) = E_t[S(T)] + \pi(t,T) \tag{2.13}$$

with $E_t[S(T)]$ being the expected spot price at maturity T and $\pi(t,T)$ the risk premium.

According to the hedging pressure theory, depending on the distribution of market participants, the futures price can be lower or higher compared to the spot price. Therefore, the theory is able to describe a futures market in contango as well as in backwardation.

2.3.2.2 Specifics of Electricity Futures Markets

The academic literature assumes that the risk premia approach is the appropriate price formation mechanism for exchange-traded electricity contracts. This point of view is mainly based on the non-storability of the commodity electricity and the resulting futures market character of all electricity markets. Therefore, the price of an electricity contract is mostly seen to include a risk premium in addition to the forecast of the future spot price.

As the theory of storage is based on the assumption of storability, it does not have to be applicable in the case of electricity. Furthermore, as noticed by Geman & Vasicek (2001), "the non-storability of power makes irrelevant (...) the notion of convenience yield, which represents the benefits accrued from 'holding' the commodity".[259]

The risk premia in electricity contracts can be both positive and negative. Empirical results indicate that risk premia in electricity markets are mostly positive, at least for short- and mid-term futures.[260] This is contrary to other markets as positive risk

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[259]Geman & Vasicek (2001), p. 93.
[260]The terminology used in this dissertation is as follows: Futures with a maturity between one and three months are considered to be short-term, with a maturity between four and twelve months as mid-term, and with a maturity over twelve months as long-term futures.

premia translate into a negative price of risk.[261] Thus, a long position in these contracts is on average linked to negative returns. A plausible economic interpretation of positive risk premia is that holders of long positions in the futures are compensating holders of short positions for bearing the price risk. Under the assumption that prices are set by industry participants – and not by outside speculators – this implies that electricity consumers are more interested in hedging than the producers are. This explanation seems to be appropriate considering that price risk is an essential risk in the short run, mainly due to frequently emerging price spikes.

Assuming that electricity consumers are mainly interested in hedging their short-term price exposure, one can argue that the sign of the risk premium can change according to the time horizon considered. Electricity consumers use short-term futures for hedging purposes while producers predominantly use long-term futures. The economic rationale behind the producer behavior may be the long-term character of investments in the energy industry. This results in demand for long-term futures to hedge cash flows far in the future to gain at least some planning reliability for investment decisions.[262] In consequence, the behavior of both consumers and producers may result in market segmentation which translates into positive risk premia in short-term and negative risk premia in long-term futures. Benth et al. (2008) develop a framework to model this effect.[263]

However, parts of the academic literature disagree with the interpretation of price differences between electricity markets or rather market segments with different trading times as risk premia. Borenstein et al. (2008), for example, argue that market inefficiencies and market power are alternative explanations for these price differences.[264] Factors such as luck or superior forecasting abilities[265] may also serve as explanations for these price differences.

Another interpretation of the price differences are forecast errors. However, in the case of longer sample periods, the occurrence of systematic forecast errors poses the question why arbitrageurs do not profit on these errors or rather whether expectations are formed rationally. To apply the ex post risk premia approach[266], one of the underlying assumptions is rational expectations; systematic forecast errors are excluded under this assumption.

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[261]Cf. Kolos & Ronn (2008), p. 623.

[262]Cf. chapter 3 for a discussion of the impact of hedging on the NPV of the investment.

[263]Cf. section 2.3.3.2 for a discussion of the model developed by Benth et al. (2008).

[264]Borenstein et al. (2008) also discuss transaction costs as potential reason for persistent price differences. However, the authors observe that at least direct transaction costs are too small in magnitude to be used as an explanation.

[265]Cf. section 4.3 for a discussion of the impact of superior forecasting abilities on returns in futures markets.

[266]Cf. section 4.3 for a discussion of the methodology applied in this dissertation and the underlying assumptions.

2.3.3 Price Formation in Commodity Futures Markets: Evidence

2.3.3.1 Empirical Evidence Commodity Futures Markets

A broad literature on the suitability of the risk premia approach and of the theory of storage as a potential price formation mechanism in futures markets exists.[267] I focus the literature review on empirical studies dealing with commodity markets and restrict the review to the past 30 years. Furthermore, I restrict the literature review on the classic studies. The empirical results on the suitability of the risk premia approach (or rather the normal backwardation theory as this is the term most often used in this context) are of primary interest for the further discussion.

Bodie & Rosansky (1980) compare returns of commodity futures with returns on common stocks. Using a sample consisting of 23 commodities traded in the United States over the period from 1950 until 1976 the authors find a positive mean rate of return of a benchmark portfolio. The return of the portfolio is found to be about the same as the mean rate of return on common stocks. When estimating the beta of their commodity portfolio the authors reject the hypotheses of the beta being equal to one at any significance level. Regarding the betas of the individual futures the most are found to have a negative beta over the sample period. Furthermore, the authors show that commodity futures seem to be a good inflation hedge. Their results indicate that stocks and futures are negatively correlated. In summary, the authors see their results as support for the normal backwardation hypothesis.

The results of Bodie & Rosansky (1980) also enlarge the empirical results of Dusak (1973). When analyzing the average returns for wheat, corn, and soybean futures over the period 1952 to 1967 Dusak (1973) finds results close to zero. By enlarging the sample period, Bodie & Rosansky (1980) find evidence on positive returns for these commodities.

Soybean, corn, wheat, cotton and cattle futures markets are investigated by Carter et al. (1983). The authors analyze weekly average futures prices over the period 1966 to 1976 and aim to evaluate the portfolio interpretation of futures. They extend the framework of Dusak (1973) and find some evidence for systematic risk. In addition, they find evidence for non-market risks with a seasonal pattern. The betas are within their framework stochastic and the market portfolio includes futures contracts.

Jagannathan (1985) aims to investigate commodity futures prices using the consumption-based intertemporal CAPM. The developed framework is tested on futures prices for corn, wheat, and soybeans over the period January 1960 to December 1978. The empirical evidence result in a rejection of the framework.

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[267]Cf. for example Carter (1999) for a recent literature survey.

The profitability of certain trading strategies in three commodity markets (wheat, corn, and soybean) is tested by Chang (1985). His data span over the period from 1951 to 1980. The obtained results are evidence for the theory of normal backwardation, i.e. the author indirectly finds that a risk premium is exchanged between hedgers and speculators. Furthermore, the author shows that the risk premia tend to become more significant in recent years when compared with earlier years and that certain speculators seem to posses superior forecasting abilities. However, Chang (1985) makes no attempt to estimate the relative size of the sources of returns.

Hartzmark (1987) rejects the theory of normal backwardation and its extension. Analyzing trading histories of individual futures traders in nine futures markets the author finds no consistent (positive) risk premia received by speculative traders. Thereby, his dataset spans over four years and is taken from a confidential file from the Commodity Futures Trading Commission (CFTC).

Using the same dataset, Hartzmark (1991) shows in a further paper that individual traders do not possess superior forecast abilities. The conclusion of the author is that trading performance is driven by luck.

Fama & French (1987) analyze price formation in commodity futures markets by examining the suitability of the theory of storage and the risk premium approach. They analyze 21 commodities (agriculture, wood, animal, and metal products); while sample periods vary, they mostly analyze data between 1966 and 1984. While finding support for the first theory, the results for the hedging pressure theory are mixed; with only marginal evidence found. Thus, the authors conclude that their results are not strong enough to make a contribution to the controversy on whether nonzero expected risk premia exist.

Bessembinder & Chan (1992) examine whether instrumental variables like Treasury bill yields and equity dividend yields, which were shown to possess forecast power in equity and bond markets, can be applied in futures markets (agriculture, metals, and currency). They show that the used instrumental variables also possess forecast power in 12 futures markets. The authors conclude that their results are consistent with time-varying risk premia.

The roles of systematic risk and hedging pressure in explaining risk premia in futures are investigated by Bessembinder (1992). Using data from equity markets and 22 financial, foreign currency, agriculture, and metal futures markets, covering mostly the sample period January 1967 to December 1989, the author finds little evidence for the first determinant but substantial evidence for hedging pressure effects.

Kolb (1996) focuses on systematic risk and returns in futures markets. The author examines 4735 futures contracts on 45 commodities with almost 600,000 daily ob-

servations. The covered sample period is 1969 to 1992. The author investigates three key hypotheses: (i) the mean returns are equal to zero, (ii) the systematic risk of futures contracts is zero, and (iii) the relationship between realized returns and systematic risk. The results of the empirical analysis are: (i) 29 of the futures have returns that do not differ significantly from zero, (ii) the mean beta is 0.0463 for physical commodity futures and only five goods have mean betas exceeding 0.10, and (iii) there is no positive relationship between realized returns and systematic risk. If anything, the returns are generally inversely related to systematic risk. However, due the low levels of systematic risk these results must be interpreted with caution.

Empirical evidence regarding the existence of hedging pressure is reported by de Roon et al. (2000). The authors analyze 20 futures markets, divided into four groups (financial, agriculture, mineral, and currency). Their dataset spans over the period January 1986 to December 1994 and consists of semi-monthly price observations. Finding evidence for hedging pressure effects, the authors show that the results are robust to market risk considerations.

Regarding energy markets, Considine & Larson (2001) test for the presence of risk premia in crude oil and natural gas markets. The authors analyze the futures contract for West Texas Intermediate crude petroleum over the period 1983 to 1999 and the natural gas futures contracts for delivery at the Herny Hub over the period 1990 to 1999. They find strong evidence for risk premia and also show that these premia rose sharply with increasing price volatility. In addition, the authors find evidence supporting the existence of convenience yields.

Wei & Zhu (2006) aim to estimate the convenience yield and the risk premium in the natural gas market of the United States. The authors use contrary to other studies forward prices instead of futures prices. The forward price data cover the period January 1991 to August 2003. Regarding risk premia the authors conclude that they are measurable and economically significant. When analyzing the determinants of the risk premia they find mixed results.

2.3.3.2 Empirical Evidence Electricity Futures Markets

Empirical results regarding the existence of risk premia in electricity contracts can be divided into two lines of research. The first focuses on short-term risk premia, mainly defined as the price difference between the hour contracts in the day-ahead and in the intraday market. The second line examines long-term risk premia, mostly focusing on the analysis of week and of month futures.

Contributions to the research on short-term risk premia are made among others by Geman & Vasicek (2001), Saravia (2003), Longstaff & Wang (2004), Boogert &

Dupont (2005), Karakatsani & Bunn (2005), Diko et al. (2006), Hadsell & Shawky (2007), Borenstein et al. (2008), Hadsell (2008), Douglas & Popova (2008) Daskalakis & Markellos (2009), Ronn & Wimschulte (2009) and Viehmann (2009). The results of this research are mostly the detection of risk premia which vary throughout the day and are highly volatile. In general, the risk premia are positive during hours of high demand.

Shawky et al. (2003), Lucia & Torro (2008), Botterud et al. (2010), Marckhoff & Wimschulte (2009), Capitan Herraiz & Rodriguez Monroy (2009), Redl et al. (2009), Furio & Meneu (2010), Kilic & Huisman (2010), Wilkens & Wimschulte (2007) Bierbrauer et al. (2007), and Kolos & Ronn (2008), among others, contribute to the research on long-term risk premia. The results are mostly positive risk premia in the short-term and mixed results for the long-term.

Prior to individually discussing the results obtained by these two lines of research, I address the most important contributions of the theoretical literature on risk premia and price formation in electricity futures markets.

Theoretical Literature

The work of Bessembinder & Lemmon (2002) is probably the most influential theoretical paper on electricity futures markets, at least according to the number of citations. The authors develop an equilibrium model for electricity forward pricing with closed form solutions. They assume that prices are determined by industry participants and that the mean and the variance of the profits are of interest for power companies. The authors derive the net demand for forward contracts, both of the producer and of the retailer. Implications of their model are negative risk premia in the case of expected low demand and demand risk. An increase of these two variables leads to an increase of risk premia which can even result in positive risk premia. Thus, the model links risk premia to risk considerations.

Benth et al. (2008) develop a model that is able to explain the dependence between the risk premia, the risk preferences and the interaction between buyers and sellers. Under certain conditions they can derive explicit solutions. The authors argue that producers are exposed to market risk over longer time periods than consumers. This has a first order impact on forward prices and the risk premia. Applying this model to the German market the authors show that the risk premia exhibit a term structure depending on the risk aversion and the market power of producers.

A model where electricity prices are explained by demand and capacity is developed by Cartea & Villaplana (2008). The model enables the authors to derive analytical expressions to price forward contracts and to calculate risk premia. When applying

the model to data from the United States, England, Wales, and the Nord Pool the authors observe that the dynamics of the risk premia are seasonal. This is according to the observed volatility of demand as the demand follows also a seasonal component. In months with high volatility of demand, forwards trade above the spot prices; in months with low volatility of demand even negative risk premia are possible.

Pirrong & Jermakyan (2008) propose and implement a model to valuate power and weather derivatives. The electricity spot price is in this model a function of two state variables: demand and fuel price. The application of the model to data from the PJM market results in upward biased forward prices. Furthermore, the authors show that the upward bias is higher for forwards with maturity in high demand periods. The authors explain the large biases with extreme right skewness of power prices which induces left skewness in the payoff distribution of the short side; a large risk premium is hence required to keep the seller of power forwards in the market. Based on their results the authors conclude that the power markets are not fully integrated with the broader financial markets.

The influence of natural gas storage inventories on the risk premia is investigated by Douglas & Popova (2008). The authors develop a model that links the effect of gas storage constraints on the higher moments of the electricity price distribution. The developed model confirms the results of Bessembinder & Lemmon (2002) and extends their model. One of the model's predictions is a negative effect of an increase in gas storage inventories – under certain conditions – on the risk premia. Testing the model on data from the PJM market the results strongly support the model. The analyzed dataset ranges from January 1, 2001 to December 31, 2004 and consists of hourly prices of the day-ahead and of the intraday market. The estimated risk premia vary throughout the day.

Support for the results of Douglas & Popova (2008) is found by van Treslong & Huisman (2009). The authors apply a different definition of the risk premia and find similar results. Thus, they conclude that the results are not influenced by modeling effects.

Daskalakis & Markellos (2009) research the topic on whether the risk premia in electricity forward contracts are affected by emission allowance prices. The trading of emission allowances within the EU ETS established a new direct production cost factor for the electricity generator, directly impacting the electricity prices. When analyzing the impact on the risk premia the authors find results that indicate that the relation is positive, i.e. they establish a link between the emission allowance spot returns and the risk premia. To establish this link they first have to obtain results for the German intraday market. When analyzing the period September 2006 to October 2007 – approximately the first year of operation of the intraday market –

the authors detect negative daily risk premia. However, the results must be interpreted as being preliminary due to the short sample period and due to the fact that liquidity during the first months of trading in the intraday market was very low.[268] Furthermore, the authors sample the data at daily frequencies. They also find risk premia in contracts traded at the Nord Pool and at the Powernext.

Short-term risk premia

Geman & Vasicek (2001) present a formalism for pricing derivatives and modeling spot price behavior for non-storable commodities. They focus on the commodity electricity due to the recent introduction of exchange-traded contracts and its unique characteristics. When analyzing data from the Western Hub of the Pennsylvania, New Jersey, and Maryland (PJM) market they find positive risk premia. Thereby, the authors compare 740 day-ahead prices with realized spot prices. Furthermore, they find evidence for higher risk premia in summer months.

Saravia (2003) analyzes the New York market which is operated by the New York Independent System Operator (NYISO). This market began operation in November 1999. During the first two years of operation market access was exclusively provided to market participants with generation capacity or who were responsible for procuring electricity. Then, in November 2001, virtual bidding was implemented, i.e. a mechanism intended to open the market to non-commercial market participants by allowing speculating on day-ahead and on intraday market price differences. The author finds positive price differences, i.e. risk premia, for these two market segments in the analyzed period. However, Saravia (2003) shows that due to speculators' participation after the introduction of the virtual bidding the risk premia decreased substantially. Thus, the results indicate that the increase of market participants leads to a more efficient market.

One of the first published academic and probably by now the most-cited empirical paper regarding short-term risk premia is Longstaff & Wang (2004). The authors analyze the PJM market over the period June 2000 to November 2002. They use a dataset consisting of hourly spot and day-ahead prices extending over 913 days. After finding significant risk premia which systematically vary throughout the day they link these risk premia to different risk factors as volatility of unexpected changes in demand, spot prices, and total revenue. They find evidence that the risk premia are positively related to these risk measures. The mean hourly risk premium is estimated at 0.59 U.S. Dollar, whereby 10 hourly risk premia are negative and 14

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[268]I exclude the sample period covered by the analysis of Daskalakis & Markellos (2009) in the empirical analysis in the next chapter as the liquidity of the intraday market was extremely low at the beginning; cf. section 4.4.1.1.

positive. However, the average daily risk premium is statistically not significant. The highest risk premia are found in the peak evening hours with around 12% of the average spot price. In general, the largerst risk premia are found during the 12 pm to 9 pm period. The authors also test the implications of the Bessembinder & Lemmon (2002) model and find support in the analyzed data. Comparing the volatility of forward and expected prices the authors find a lower volatility of the forward prices. They interpret this observation as a further evidence for risk premia in the forward prices. The conclusion of the study is that forward prices in the PJM market are rationally determined by risk-averse market participants.

Boogert & Dupont (2005) analyze the relation between the intraday and the day-ahead market in the Netherlands. The primary aim of their paper is to test the effectiveness of the policy of the Dutch regulator to prevent trading across these two markets. Trading based on a spread strategy is seen as gambling by the regulator which therefore implemented a system to prevent this kind of trading. The rationale is preventing imbalances in the Dutch market. Using a dataset covering the period January 2001 to December 2003 the authors find that the price difference between the two markets, i.e. the risk premia, are slightly positive but not statistically significant. To conduct this analysis the prices from the intraday market which have a frequency of 15 minutes are aggregated to hourly prices. When testing the profitability of two basic trading strategies (selling electricity in the day-ahead market and buying it in the imbalance market and buying electricity in the day-ahead market and selling in the intraday market) based on these risk premia the authors find weak evidence for a profitability. Thereby, the profitability is tested over the whole period, over each single year, and over each single hour.

The focus of Karakatsani & Bunn (2005) is on the day-ahead risk premia in the British market. The authors use a dataset from June 2001 to June 2003 in order to verify the existence of risk premia. They classify the half-hourly trading periods in two homogeneous clusters, peak (7am – 7pm) and off-peak (7pm – 7 am), regarding them as fairly homogeneous in terms of hedging incentives, demand characteristics, and operating plant technologies. The authors find significant risk premia which change sign, depending on whether peak or off-peak hours are analyzed. As potential explanations for this change in sign they identify the asymmetric positions of generators and suppliers towards risk and the possibility of an intra-day variation. The estimated risk premia are positive on 73% of the days in peak periods; in off-peak periods the risk premia are negative on 75% of the days. For peak periods the excess capacity on the previous day, financial risk (spot volatility on the previous day, spread on the previous and current day), and lagged spot prices are found to be reflected in the risk premia. In addition, the authors calculate the ex ante risk pre-

mia. These risk premia are in their magnitude similar to the ex post risk premia but very sensitive towards the underlying assumptions regarding the spot price model.

Diko et al. (2006) analyze the period January 2001 to August 2005 regarding the existence of risk premia in three European electricity markets. They use OTC prices and exchange (intraday) prices. The investigated markets are Germany, the Netherlands, and France. The OTC prices are provided by Platts, the leading global provider of energy and metals information. The OTC data consist of day-ahead prices (not for weekends) for base, peak, and off-peak periods as defined by the corresponding exchange; the intraday prices are directly obtained from the exchanges. They find statistically significant positive risk premia in all markets during peak hours. For the German market they also find negative risk premia in the off-peak period. Furthermore, the authors show that a time-evolution of the risk premia can be observed. The evolution is expressed in a clear reduction of the risk premia with progressive maturity of the markets. When analyzing a potential term-structure of risk premia the results indicate that, as the time-to-delivery decreases, the long-term and medium-term risk premia increase. The results concur with the Bessembinder & Lemmon (2002) model.

Hadsell & Shawky (2007) examine the New York wholesale market over the period January 2001 to March 2005. When analyzing the hourly risk premia the authors use data from two delivery zones, the New York City and the Genesee zone. Finding significant risk premia they show that the magnitudes vary on a daily, weekly, and monthly basis. Furthermore, the risk premia are found to be different in magnitude across the two zones. The authors argue that this could be due to the fact that the NYSIO markets are not fully integrated within the wider financial market. The introduction of virtual bidding is shown to be associated with lower premia in off-peak hours and higher premia in peak hours. Thus, the effectiveness of speculators altering the risk premia seems to be limited. This is contrary to the expectations at the time of implementation of the virtual bidding mechanisms and also to the empirical results obtained by Saravia (2003) for the first years of operation.

Borenstein et al. (2008) analyze the trading period prior to the occurrence of a significant event in the still young history of deregulated electricity markets, namely the collapse of the Californian electricity wholesale market in 2000. Two years prior to the collapse the Californian market had the two typical market segments, namely the day-ahead and intraday market, with trading of contracts for the same time and location. The authors report large price differences between these two market segments. In addition, they argue that the price differences were ex ante predictable. However, they exclude the interpretation of this price differences as risk premia caused by risk aversion due to (i) the regular change in sign, (ii) the opportunity

to diversify the risk, and (iii) the high magnitude. They rather attribute the price differences to trading inefficiencies and market power.

The short-term risk premia in contracts traded for delivery in New England are examined by Hadsell (2008). The New England market is operated by the New England ISO and spans over eight zones which are all analyzed by the author. The dataset consists of the price for peak hours (7am to 11pm) on non-holiday days in the period January 2, 2004 to December 31, 2007. The main findings are that the risk premia are positive and consistent over the years. Furthermore, there is evidence that the risk premia are higher in June and lower in August and October. The author also reports that the risk premia are stable in their magnitude over the analyzed period. Furthermore, there is evidence that the ex ante risk premia are positive in all months.

Ronn & Wimschulte (2009) conduct a first analysis of the German spot market using data from August 2002 to September 2007 from the day-ahead and block contract market. In addition, using data from June 2004 to September 2007, the Austrian market located at the Energy Exchange Austria (EXAA) is analyzed. The posed question is whether there is a risk premium in contracts traded at the EXAA with delivery in Germany. This analysis is justified due to the fact that there is no congestion between the Austrian and the German market. Regarding the German market, the authors find positive risk premia in the block contract market. In particular the risk premia in contracts with the longest time-to-delivery are found to be high and statistically significant. For contracts with delivery on non-working days the results suggest that the risk premia are on average negligible. In addition, the market price of risk is computed for both investigated markets.

Viehmann (2009) estimates risk premia in the day-ahead market of the EEX. The author uses price data from the day-ahead market and from the Austrian electricity exchange EXAA. The EXAA data are used as a proxy for data from the OTC market, in which trading takes place prior to the EEX but price data are not publicly available. The trading in the OTC market mainly takes place – according to the author – between 8 am and 12 pm on the day prior to the delivery day. Only standardized block contracts can be traded; the traded volume seems to have the same magnitude as in the day-ahead market of the EEX. Thus, the OTC-market can be interpreted as a forward market in relation to the day-ahead market. As the auction on the EXAA takes place between 10.12 am and 10.15 am and contracts with delivery in Germany are traded in this auction the OTC prices and the EXAA prices coincide due to arbitrage possibilities. Consequently the EXAA prices reflect the OTC market approximately two hours before the auction on the EEX starts. Taking this point of view the author finds – covering the sample period October 2005 to

September 2008 – hourly risk premia that are significantly different from zero and both positive and negative. However, the overall mean of the daily risk premium is statistically not different from zero. The largest positive risk premia are found in evening peak hours during winter months; they amount to around 10%. The average risk premium in contracts with delivery in four evening hours is shown to be more than eight times higher during the winter months (November to February) as during summer months (March to October). This is the time period with the year's highest electricity consumption levels.

Long-term risk premia

Shawky et al. (2003) analyze futures traded in the New York Mercantile Exchange (NYMEX) with delivery at the California-Oregon Border. Their dataset includes daily data for month futures which start trading six months before delivery. The data cover the years 1998 and 1999. Trading in the electricity futures started already in 1996 but due to the low liquidity, the inexperience of the market participants and the lack of deregulation in other markets the authors exclude the data from the first two years of operation. As result the authors find positive risk premia which are estimated to be 0.1328% per day whereby the relative risk premia are defined as the quotient of the risk premia and the spot price at delivery. The risk premia seem to increase with increasing time-to-delivery. When analyzing the trading patterns in electricity futures the authors show that volume gradually increases over the life of the contracts, i.e. the short-term futures show the highest traded volume. Regarding the open interest an increase with increasing life of the contracts is also found. Beyond the 30-day mark a significant drop in open interest appears, indicating that the majority of the contracts are closed out.

Data from the Nord Pool are analyzed by Lucia & Torro (2008). Their dataset covers the period January 1, 1998 to October 28, 2007 and consists of the four closest-to-delivery week futures. Weekly observations of the futures prices are analyzed. The authors find significant positive risk premia in the short-term futures. It is shown that the magnitude and the significance of the risk premia varies over the year. The risk premia are highest in winter months and zero in summer months. The risk premia are positive 60.5% of the weeks in the dataset. Furthermore, the authors link the risk premia to unexpectedly low reservoir levels. The authors also show that a supply shock – probably caused by a significant reduction in hydropower production due to abnormally low water inflows – hit the market around the end of year 2002 and changed the market environment. Evidence is reported that prior to the occurrence of this event the risk premia were related to the variance and to the skewness of the future spot prices as predicted by the model of Bessembinder & Lemmon (2002).

After the supply shock this relation broke down.

Botterud et al. (2010) report results concerning week futures traded at the Nord Pool. The authors find statistically significant positive risk premia in futures with a time-to-delivery up to six weeks covering the sample period 1996 to 2006. For their analysis they use the closing price on the last day of trading in each week for the week futures and the average weekly price on the day-ahead market. The authors identify differences between the supply and demand sides in risk preferences and the ability to take advantage of short-term variation in prices as potential explanations for the relationship between spot and futures prices. Furthermore, they link the risk premia to the physical state of the system, expressed by the hydro inflow, reservoir levels and demand. In addition, the authors argue that due to the high share of hydro power with large reservoirs not only the hedging pressure theory but also the theory of storage are relevant for an analysis of the relationship between spot and futures prices. The convenience yield in the weekly futures contracts is then estimated. The result is an average net convenience yield which is negative over all holding periods. The convenience yield is positive in the first half of the year when reservoir levels are low and negative in the second half when reservoir levels are normally high. Also the risk premia exhibit a (less distinct) seasonal pattern.

Marckhoff & Wimschulte (2009) analyze Contracts for Difference (CfDs) traded at the Nord Pool. CfDs are cash-settled future contracts and allow to hedge against price differences among different delivery areas. This is of interest in the case of congestion of electricity transmission lines. As a result different prices evolve in connected grid zones. CFDs were first traded at the Nord Pool at the end of 2000. The authors analyze the period 2001 to 2006 and find significant short-term positive risk premia and negative long-term risk premia. These risk premia exhibit significant variability in terms of sign and magnitude. When testing the model of Bessembinder & Lemmon (2002) they find that the implications can be confirmed for the risk premia in the CfDs.

An analysis of the Iberian power futures market is conducted by Capitan Herraiz & Rodriguez Monroy (2009). The dataset of their study starts in August 2006 and ends in July 2008. Month, quarter, and year futures are analyzed, however, no statistically reliable results can be obtained due to this short time period. Thus, the reported results need to be seen as preliminary. In addition, the market started operation in July 2006. Problems such as the inexperience of market participants and the low liquidity question the results even more. The authors analyze the risk premia from an ex post perspective and show that the futures price is slightly upward biased, implying positive risk premia. They estimate the risk premia as a percentage of the futures price. When testing for potential drivers of the risk premia the authors find

little evidence for the implications of the Bessembinder & Lemmon (2002) model. In summary, the authors conclude that energy markets show a limited level of market efficiency.

Redl et al. (2009) investigate the relevance of systematic forecast errors in the price formation process in electricity forward markets. The authors analyze data from the EEX and the Nord Pool. They find that the prices of year futures at the EEX are influenced by past spot prices. They term this as an adaptive expectation formation behavior which results in a biased forecasting power of the futures. From an ex post perspective they show significant positive risk premia in month futures traded at the EEX. Parts of the risk premia are explained by risk assessment measures. However, an unexplained part remains and hence inefficiencies are not ruled out by the authors.

Furio & Meneu (2010) analyze the Spanish electricity market for long-term risk premia. They use both the ex ante and the ex post approach. Due to the fact that the Spanish futures market was launched only in July 2006 the authors use data from the OTC market. They analyze the first-to-deliver month forward which is a base load contract with the underlying being the Spanish (day-ahead) spot market. This contract was traded for the first time in February 2003 for delivery in March 2003. Price data are obtained by Reuters. Covering a sample period between February 3, 2003 and August 31, 2008 they find that overall the ex post risk premia are negative but not statistically significant. It is observed that the risk premia were negative over the period from November 2004 to February 2006 and positive thereafter. The authors also show that the sign and magnitude of the ex post risk premia are dependent on the unexpected variation in demand and on the unexpected variation in the hydroelectric capacity. In addition, both the ex post and the ex ante risk premia are negatively related to the variance of spot prices as predicted by the Bessembinder & Lemmon (2002) model. Furthermore, the authors propose a forecast model for electricity spot prices at a monthly level.

Kilic & Huisman (2010) analyze whether power production flexibility is a substitute for the storability of electricity. To answer this question they analyze futures prices from Belgium, Germany, the Netherlands, and the Scandinavian countries, i.e. the Nord Pool. As results the authors find that futures prices from markets with flexible power supply behave according to the expectations theory. The hypothesis underlying their study is contrary as production flexibility is supposed to result in futures prices that are more in line with the theory of storage. Thus, the above relation is denied. However, their results confirm the existence of risk premia in various electricity markets.

Wilkens & Wimschulte (2007) report first results on risk premia in the German

futures market. The authors analyze the pricing of futures traded on the EEX between June 16, 2002 and December 31, 2004. They restrict their study to month futures with a maturity of up to six months. After estimating ex ante risk premia they compare their results with ex post risk premia. To estimate the ex ante risk premia they investigate the performance of one- and two-factor reduced-form models. The authors find positive risk premia, both from an ex ante and from an ex post perspective. The risk premia are highly volatile and regularly change in sign.

Bierbrauer et al. (2007) aim to provide an overview on the most promising and established models in the literature for the forecasting of electricity spot prices. They test these models on data from the EEX and identify three models which best fit the data. When using the three models for the forecast of ex ante risk premia they find positive risk premia in the short- and mid-term and negative risk premia in the long-term contracts.

Estimating the market price of risk is the aim of Kolos & Ronn (2008). For this purpose, the authors first estimate the risk premia in energy commodities. Using a dataset from the EEX covering the period 2002 to 2006, the results are positive risk premia in the case of electricity. This concurs with the results of Wilkens & Wimschulte (2007).

Chapter 3

A Project Finance Valuation Tool

Despite the popularity of project finance in practice, there is still only limited relevant academic literature available, or rather the published literature focuses mainly on the qualitative aspects of this financing method. This dissertation aims to contribute to the gradually evolving quantitative literature. Hence, I develop together with two other doctorate students a project finance valuation tool which is based on stochastic cash flow modeling and advanced forecast models.

In this chapter I introduce the newly developed project finance valuation tool. In the fifth chapter the tool will be used to quantify the impact of model complexity on the valuation results within a case study; in this chapter I focus on a discussion of the valuation tool itself. However, I also already examine some specifics of the case study. In particular the cash flow equation underlying the case study is discussed. At the beginning, I address the general functionality and computational implementation of the valuation tool. Then, the separate steps of the valuation process are discussed. Thereby, I distinguish between three process steps, namely input, computation, and output. I discuss the valuation results, i.e. the NPV distribution and the cumulative default probability, and their presentation. Furthermore, I discuss the status quo of the tool and its present limitations. In addition, I focus on the forecast models applied within the valuation process. An extended excursus addressing time series modeling and forecasting is therefore provided at the end of the chapter. The forecast models implemented in the valuation tool are presented and discussed. I conclude the chapter with a summary of the capabilities of the valuation tool and an outline of promising avenues for future research.

This chapter aims to answer the following three key questions:

- What are the intended capabilities of the project finance valuation tool?

- How does the valuation tool work in detail, which forecast models are used for the computation, and what are the final computation results?

- What are the present limitations of the developed project finance valuation tool and how could future research help in resolving these limitations?

3.1 Research Question

The newly developed project finance valuation tool is based on stochastic cash flow modeling. In order to model the future cash flows, I select the stochastic modeling approach as a sophisticated modeling method, established in the financial literature. Results obtained through this approach are able to answer questions beyond the possibilities of other modeling techniques. One of the main advantages is the possibility to estimate ex ante default probabilities of a project finance investment. The implemented forecast models are based on recent literature and represent the current standard models. For example, for the forecast of level data these are autoregressive moving average (ARMA) models, for volatility forecasts the general autoregressive conditional heteroskedasticity (GARCH) model, and for correlation forecasts the dynamic conditional correlation (DCC) model. The research question underlying the implementation of all these models is how to program an efficient computer algorithm, which is able to deal with these data-intensive computation tasks.

The motivation behind the development of the project finance valuation tool is twofold. First, the valuation tool is intended to be a general, sophisticated valuation model based on stochastic cash flow modeling and the most recent forecast models. Second, the valuation tool is intended to be applicable to specific valuation tasks and still employable by non-trained users. Thus, the tool is to be used for both research as well as practical projects. Another aim is to design the tool as general and variable as possible so as to be open for future extensions. In addition, the tool has been designed in a modular framework in order to allow future extensions by multiple developers. Regarding the valuation of actual projects, the tool is practicable for the valuation of power plant ventures financed via project finance.

Furthermore, in order to assure meaningful results, the calculation of the cost of capital is of crucial importance. To obtain unbiased estimates for the NPV, one needs to take into account the limited lifetime of the project and the resulting changing capital structure.

Another aspect to be taken into account during the development of the tool is that of the significant data volumes. Both – the input data necessary for the valuation and the data generated within the valuation process – lead to a data-intensive computation. In addition, correlation structures and non-analytical distributions are intended to be implemented. The appropriate handling of the resulting data volumes is critical for an efficient processing time of the valuation tool.

3.2 Functionality and Implementation

3.2.1 Introductory Remarks

The tool developed within this dissertation is intended to valuate project finance investments. The tool is basically a stochastic cash flow modeling tool.[1] On the basis of a general cash flow equation the tool combines several separate input and output factors; forecasts for level data, volatilities, and correlations are derived from various forecast models. It then simulates a predefined number of future cash flow paths, which are aggregated to probability distributions of the expected cash flows at certain future point-in-times. Based on these cash flow distributions the tool computes the probability distribution of the expected NPV. In addition, it computes the cumulative default probability over the project's lifespan. Moreover, various cover ratios and default probabilities are calculated for every future point-in-time of interest as well. The computation is performed with Matlab. However, the user specifies the input parameters and starts the valuation process in Microsoft Excel. The results are stored in an Microsoft Excel spreadsheet and in an output file. The output file is displayed at the end of the valuation process. The output file summarizes the valuation results as well as the underlying input parameters, factors, and the applied forecast models.

In order to simplify the terminology, I will abbreviate the valuation tool as PFVT (Project Finance Valuation Tool).

Starting with the development of a basic cash flow tool[2], the functionality of the PFVT has been extended over time, mainly because of the participation of two of the involved doctorate students in a research cluster dealing with energy.[3] It was first extended into a valuation tool for project finance and second into a valuation tool

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[1]Cf. section 2.1.2.5 for a discussion of stochastic cash flow modeling.

[2]The PFVT is part of an extended research project. At the moment three doctorate students are involved in the tool's development.

[3]Two of the doctorate students involved in the development of the PFVT are members of the research group "Energy 2030". Both the research group and the doctorate students are supported by the International Graduate School of Science and Engineering (IGSSE) at Technische Universität München (TUM).

for power plant investments financed via project finance.[4] Despite all extensions, the aim to preserve high flexibility remained valid. Thus, the PFVT can now be used to value investments both from the equity and from the debt perspective. In general, the equity side is of more interest when examining capital investments. However, in the case of project finance, the debt side – as discussed in the second chapter – also heavily relies on an appropriate modeling of the expected cash flows. Thus, I aim to cover both perspectives, designing the PFVT in accordance.

The present chapter is primarily devoted to a technical description of the PFVT, as the fundamentals and specifics of stochastic cash flow modeling are already discussed in the second chapter. Basically, the functionality of the PFVT can be described in three broad process steps. I term these process steps also modules, as each process step is programmed in a separate source code module. The three modules are the input module, the computation module, and the output module. The input module is the interface between the user and the PFVT, where the specification of the input parameters and of the project specifics takes place. The computation module is the process step where the forecasts and the Monte Carlo simulations are performed. Finally, the output module is the part where the obtained results are aggregated and where an output file is computed.

3.2.2   Functionality of the Tool

The aim of this section is to provide an overview of the broad functionality of the valuation tool and to show the logic of the valuation process. A detailed discussion of the respective valuation steps is to be found in section 3.3.[5]

Figure 3.1 depicts the three broad process steps input, computation, and output. The single process steps within the valuation process are schematically shown in the figure as well.

The first step of the valuation process consists of the specification of the input parameters. These parameters comprise the general simulation procedure, the specifics of the project, and the applicable forecast models.[6] After the completion of the parameter input the user starts the valuation process. No further interventions by the user are necessary after this step. In a second step, depending on the selected forecast models in the first step, historical time series stored in the tool are uploaded. This step is optional. Together with the input parameters, the time series are then

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[4]Cf. Weber et al. (2010) and chapter 5 for first valuation results obtained by the PFVT.

[5]It is the December 2009 version of the PFVT that is described in this chapter and applied for the valuation of the power plant venture in the case study in the fifth chapter.

[6]Cf. figure 3.1 for a summary of the input parameters. Cf. also the excursus in section 3.5 for a discussion of the implemented forecast models.

Figure 3.1
Schematic Functionality Project Finance Valuation Tool
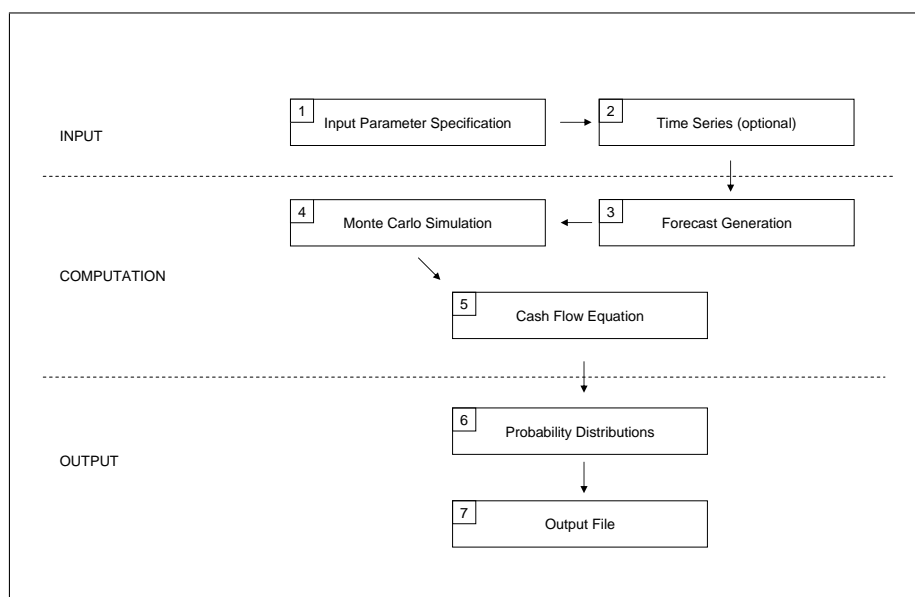
Source: Own work.

processed from the input to the computation module. In this module, in a third step, the forecasts are computed based either on the specified input parameters or the historical time series and the selected forecast model. Afterwards, in a fourth step, the forecast of the single input parameters are used for a Monte Carlo simulation, i.e. the generation of random numbers. The results of this step are linked in a fifth step with the cash flow equation underlying the valuation process. After completion of the simulation procedure the resulting data are transferred from the computation module to the output module where, in a sixth step, the probability distributions based on the cash flow paths are constructed. In addition, various ratios and probabilities are computed within this process step. Afterwards, these data are stored both in an output file and in a Microsoft Excel spreadsheet. In a seventh and last step the resulting output file summarizing the valuation results and the input parameters is displayed.

Depending on the selected parameters, in particular on the number of iterations, the whole valuation process can take from a few seconds up to a few hours.[7] After the completion of the valuation process the output file is automatically displayed.

Two steps in the valuation process – the input parameter specification and the linking of the input factors cased on the cash flow equation – deserve closer attention. These

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[7]After the input of the relevant parameters the user sees a time bar with the progress of the valuation task. This enables the estimation of the remaining processing time.

two steps are important as adjustments and manipulations within the valuation process can solely take place within these steps. Other process steps and associated modules are general parts of the valuation tool, being used independently of the specific valuation task.

The input parameter specification is the first process step in which the fundamentals of a valuation task can be manipulated.[8] Based on the specified parameter constellation, different valuation results are obtained, allowing the analysis of the valuation results depending on the specific input parameter combination. Within the case study, the sensitivity of the valuation results to changes of certain input parameters is of particular interest. I distinguish between two dimensions of input parameters when examining the results of the case study, namely parameters regarding the simulation procedure and parameters regarding the applied forecast models.

The linking of the input factors based on the cash flow equation is the second process step where manipulations are possible. In this step the input factors of a specific valuation task are combined based on a specified algebraic relation, i.e. the cash flow equation. A manipulation of the cash flow equation can have a significant impact on the valuation results. At the moment, the cash flow equation is implemented in a general form within the valuation tool. The user cannot perform any manipulations unless the source code has been modified. However, it can, for example, be advantageous to implement a growth factor in one of the input-output-relations as this mirrors the reality. Some of the desired specifications can be implemented indirectly, by re-specifying the input parameters. However, a manipulation of the cash flow equation is a more general and lasting manipulation. Thus, the implementation of a possibility to manipulate the cash flow equation at the input parameter level is one of the many potential future extensions of the valuation tool.

3.2.3 Implementation

Li (2000) correctly states that "the concept of simulation is relatively simple, but writing the computer code to simulate the data and interpreting results are difficult".[9] The implementation of a valuation tool based on stochastic cash flow modeling becomes in particular difficult due to the fact that common computer applications as Microsoft Excel are not practicable for broader stochastic tools. Advanced programming languages need to be used for applications of this kind.

The PFVT is programmed in Matlab, a powerful programming language for numerical applications. Matlab stands for **mat**rix **lab**oratory and is a numerical computing

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[8]Default parameters for a particular valuation task can be stored in a separate Microsoft Excel spreadsheet.

[9]Li (2000), p. 87.

environment often used in the context of simulation analysis.

The source code of the PFVT consists of separate modules in order to maximize the flexibility of the tool for future extensions. This flexibility also allows the simultaneous further development of the tool in several directions while securing the stability of the tool.

One of the aims when developing the PFVT was easy handling. This is why the tool is designed in a way that the user does not need to use Matlab; he or she can instead calibrate the PFVT via an easy-to-use Microsoft Excel spreadsheet. On this spreadsheet, the user is able to define all input parameters and then to start the valuation process. However, the Microsoft Excel spreadsheet merely serves as a graphical front-end. The whole computation process is performed in Matlab.

3.3 The Valuation Tool

I address the specifics of the valuation process in chronological order. First, I discuss the input module, afterwards the computation module and at the end of this section the output module.

3.3.1 Input

3.3.1.1 Input Parameters

Within the input module the user has first to specify the input parameters regarding the general simulation procedure and second the input parameters and factors of the specific project.

The necessary simulation parameters mainly concern the Monte Carlo simulation and the output of the simulation results. The number of iterations and the frequency of the cash flow calculation are of critical importance. Additionally, the desired frequency of the cash flow distributions reported and the time resolution which determines how often the cash flow is analyzed need to be specified. The duration of the simulation procedure significantly depends on these input parameters, in particular the number of iterations has a significant impact on the computation time.[10]

The specific project input parameters and factors consist of measures concerning a) the general project setup, b) the relevant input and output factors, c) the relation between the input and output factors, and d) the desired forecast models regarding

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[10]Cf. section 5.3.1 for a discussion of the computation time in dependence of the number of iterations.

the single input factors.

Regarding the specific project parameters the user, in a first step, has to define the general project setup which includes, among others, the lifespan of the project, the financing structure of the project, and the depreciation period. In a second and third step, the input and output factors and the relation between them are specified. In a fourth step, the factors related to the forecast of the parameters are defined. I have implemented several forecast models which are shortly introduced in section 3.3.2.2 and then discussed in more detail in section 3.5. Historical time series of interest rates, exchange rates and other assets are included in the PFVT. These time series can be used for the estimation of the required parameters for the forecast models. However, beneath input and output factors with historical time series, the PFVT allows the manual input of the forecast-relevant parameters as well. The user may also choose between different distributions, e.g. rectangular or triangular distributions for the parameter forecasts. This enables the consideration of non-Gaussian distributed factors being normally one of the main drawbacks of simple simulation procedures.[11]

Regarding the number of input and output factors and other relevant factors, the programming of the PFVT is rather flexible. After a specification of the required number of factors, the PFVT dynamically adopts to the necessary inputs.

Table 3.1 contains a summary of the parameters concerning the general project setup, the simulation procedure and the project's specifics which might be defined by the user for a specific valuation task.

3.3.1.2 Input Data

Historical data for various interest rates, stock index, and commodities are stored within the PFVT. The data are obtained by Bloomberg and updated when necessary.[12] An extension of the available data is possible when necessary as well.

When the user chooses to forecast a certain parameter based on the historical time series, the stored data are sent from the storage module to the forecast module. In the latter module the parameters of the time series, i.e. the mean and standard deviation during a certain time period in the past, are estimated.[13] These parameters are then used for the forecast process.

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[11]See for example Nawrocki (2001).

[12]The update of the data takes place manually.

[13]At the moment, the estimation procedure extends over the whole length of the available historical time series.

Table 3.1
Summary Input Parameters

Input Parameters regarding …		
… Project Setup	*… Project Modeling*	*… Simulation Procedure*
Initial Investment	Interest Euro	Life-span Simulation
	Interest Dollar	Time resolution
Ratio Debt	…	
Ratio Debt Euro		# Iterations
Ratio Debt Dollar	Exchange Rate 1	
Ratio Debt 3. Currency	…	Cash flow frequency
Amortization Time	Output 1 Price	
Tax Rate	Input 1 Price	
	Ratio Input 1 to Output 1	
Capacity	….	
Load Factor		
Availability Factor	Fixed Cost	
# Outputs		
# Inputs		
# Fixed Costs		
Variable Costs (% Revenue)		
Variable Costs per Unit		

Source: Own work.

3.3.2 Computation

3.3.2.1 Cash Flow Equation

The PFVT relies on the direct valuation method, implying that no accounting issues are taken into consideration. The computation is based on the specified input factors and the underlying cash flow equation.

The cash flow equation is the starting point of an appropriate valuation process. The equation not only links the specified input and output factors but also introduces the project's cost and financing structure into the valuation process.

In general, I distinguish between six constituent parts of a cash flow equation:

1. Revenue,

2. Input factor costs,

3. Variable costs,

4. Fixed costs,

5. Cost of debt, and

6. Tax.

Figure 3.2
Underlying Cash Flow Equation
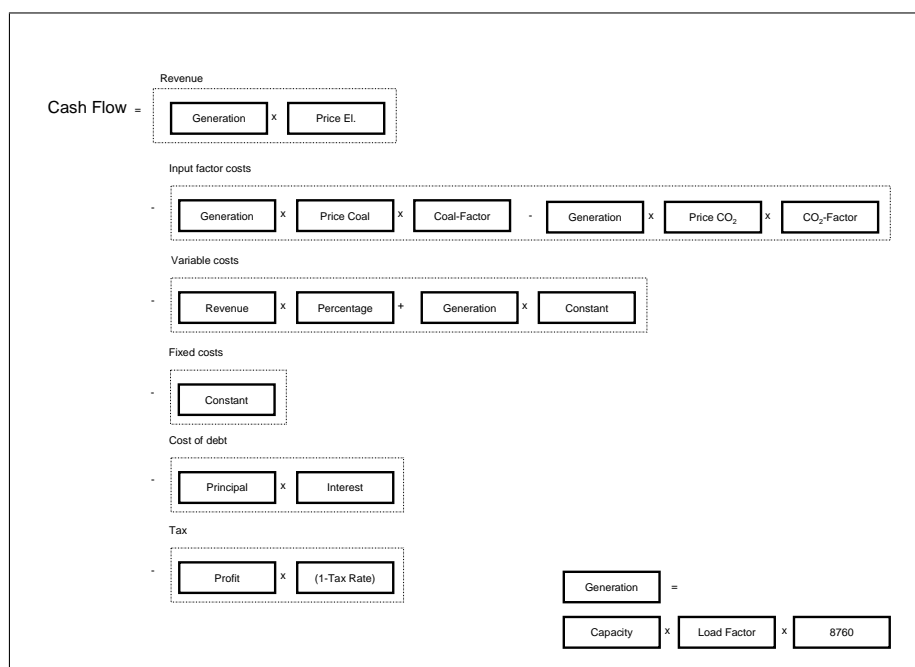
Source: Own work.

I take the cash flow equation underlying the case study in the fifth chapter to discuss the single parts of a general cash flow equation. The project of interest is a coal power plant. Figure 3.2 schematically depicts the cash flow equation. The six general parts of a cash flow equation defined above are marked with dashed boxes in the figure.

The first part of the cash flow equation, the revenue, consists – in the case of the coal power plant – of one output factor, namely electricity. The revenue is calculated as the product of the electricity price and the generated electricity in the period. Both the electricity price and the generated output are normally modeled as stochastic factors. In the case study the electricity price is modeled based on the historical time series and on an appropriate forecast model. The output is calculated as the product of capacity, the load factor, and the number of hours in the period. The load factor is a stochastic factor.[14]

The input factor cost, the second part of the general cash flow equation, consists of two input factors, namely coal and emission rights. The factor cost is calculated as the product of the electricity output and the factor cost. The defined input-output-relation is of critical importance. In the case study, both the coal and emission cost are modeled based on historical data and on an appropriate forecast model.

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[14]Cf. section 5.2.1 for a more detailed explanation of the single factors.

The third part, the fixed costs, consists of a fixed amount which is defined at the beginning of the valuation process and then used over the whole lifespan of the project. These costs are seen as non-stochastic. However, a growth factor (also negative) or a stochastic evolution can be easily introduced.

The variable cost as the fourth part of the general equation is modeled as a percentage of the period's revenue in the period. Normally the percentage remains constant over the whole lifetime of the project. In addition, a term adding a fixed amount per generated unit of electricity is implemented.

Of particular importance is the modeling of the cost of debt, the fifth part. In the case study I assume annuity debt, i.e. the debt is paid back in equal amounts over the lifespan of the debt contract. In addition, I assume that debt in two currencies is provided to the project, namely in Euro and in U.S. Dollar. The resulting U.S. Dollar payments are then variable as they are calculated in each period as the product of a fixed amount and the current exchange rate.[15]

The sixth part, the tax, is calculated based on a defined tax rate as the product of the earnings before tax and the tax rate.

A generalization of the cash flow equation can be achieved through the definition of further input parameters. Given the possibility to define the number of input and output factors variable, a second output factor, for example, can be easily added. At the moment, the design of the tool allows the implementation of five input and five output factors. However, the complexity and the computation time of the valuation process grows with the number of input parameters.

3.3.2.2 Input Parameter Forecast

The future development of the factors influencing a project's cash flow is of huge importance. Since this development is ex ante unknown, different kinds of forecast models need to be applied to obtain estimates for the future values. However, not only the absolute future values of the influencing factors are of interest. To perform a consistent Monte Carlo simulation, the future variance and correlation structures between the single input factors have to be estimated as well. The specific models implemented within the PFVT are discussed in section 3.5, in an excursus on time series modeling and forecasting. Thus, I only list the implemented forecast models here.

The following forecast models are implemented within the PFVT:

For mean values:

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[15]It is intended to implement more flexible debt contract features in the recent future.

1. Random walk,

2. ARMA, and

3. Mean reversion.

For volatilities:

1. Historical volatility,

2. GARCH,

3. Glosten, Jagannathan and Runkle – Exponential General Autoregressive Conditional Heteroskedasticity (GJR-GARCH), and

4. Exponential General Autoregressive Conditional Heteroskedasticity (EGARCH).

For correlations:

1. Historical correlation, and

2. DCC.

When a certain forecast model is applied, two possibilities for parameter specification exist. First, the parameters are manually specified by the user. Second, the parameters are estimated based on the historical time series stored within the PFVT.

When the parameters are manually specified the user in general needs to specify the mean value and the volatility of the relevant factor. In addition, the distribution may be specified as well, in particular when non-analytical distributions as the triangular distribution are preferred. Furthermore, the correlations of the relevant factor with the other factors of interest need to be specified.

When the parameters are estimated based on the historical time series the user has to specify a certain forecast model. Afterwards, the necessary parameters are automatically estimated.

3.3.2.3 Monte Carlo Simulation

The Monte Carlo module is the part of the PFVT where in a first step the generation of random numbers and in a second step the simulation of the cash flow paths takes place. The stochastic input factors (with the probability distributions generated within the forecast module) and the non-stochastic factors are combined in this module to single cash flow paths. The computation time is heavily dependent on the defined lifespan of the project, the frequency of the cash flow distributions and the

number of iterations. At the end, the results are stored in a data matrix and sent to the output module.

The functionality of the Monte Carlo module consists in a first step in the determination of a point estimate for each stochastic input factor for every future point-in-time of interest. Therefore, a random value form the probability distribution of the specific input factors is determined, e.g. drawn. The combination of these single point-in-time point estimates based on the cash flow equation results in a single cash flow estimate. The repeating of this procedure for all selected point-in-times results in a cash flow path. These cash flow paths are then combined to probability distributions of the cash flows in the computation module which will be explained later.

The core of the Monte Carlo module is the random number generator. This generator is critical as it is highly important that the generated random numbers are independent. I use the random number generators implemented in Matlab. For uniform distributions this is a generator developed by Marsaglia (Marsaglia & Zaman (1991)). For normal distributions, it is a generator developed by Marsaglia as well (Marsaglia & Tsang (1984)).

3.3.2.4   NPV Calculation

As already discussed in the second chapter, the calculation of the NPV is not a trivial task due to the non-stability of the relevant discount rate. Usually, the leverage of a project finance investment changes over time and hence the risk and the cost of capital of the project change at the same time. Also the determination of the leverage is not straightforward as it is not clear whether to use market or book values.[16]

The first problem, the non-stability of the discount rate, is faced within the PFVT by the recalculation of the discount rate in every point-in-time when a cash flow probability distribution is calculated. Based on the actual capital structure the cost of equity are estimated and the WACC then newly calculated. It is to expect that the WACC decreases with increasing time.

The second problem is solved by applying the quasi-market valuation which is discussed in section 2.1.2.2.

The NPV calculation routine applies the estimated WACC to every cash flow path to calculate a point estimate of the NPV. The combination of the point estimates results in a probability distribution of the NPV.

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[16]Cf. Esty (1999) for a discussion of these problems.

3.3.3   Output

3.3.3.1   Output File

The output module consists of two parts. The first part is responsible for the calculation of the cover ratios including the default probabilities. The second part serves the compilation of the output file.

The output file contains three sections:

1. Profitability measures,

2. Cash flow distributions, and

3. Input parameters.

The average volume of the output file is approximately 100 pages. The size of the output file mainly depends on the selected display resolution; one cash flow distribution fills one page.

The reported measures in the first and in the second section of the output file are discussed in the next section. The third section contains a summary of the input parameter values, as defined by the user or estimated based on the historical time series, and the underlying forecasts of the individual factors over the valuation horizon.

The summary of the input parameters contains a) an overview of the parameters concerning the simulation procedure, b) the models and a graphical depiction of all input parameters defined as stochastic, and c) a graphical depiction of the remaining debt capital.

In addition, the simulated cash flow paths and the calculated NPV values are stored in a Microsoft Excel spreadsheet.

3.3.3.2   Output Data

The first section of the output file, the part regarding the profitability measures, contains (1) the probability distribution of the project's NPV and (2) the estimated cumulated default probability.

The second section, the part regarding the cash flow distributions, consists of one page for each point-in-time for which a probability distribution of the cash flow was requested. The output page contains:

1. the probability distribution of the free cash flow to equity (FCFE)[17],

---

[17]The FCFE is the default setting in the PFVT. However, also the FCFF can be estimated and displayed.

2. the default probability in the certain period,

3. the cash-flow-at-risk at three confidence levels,

4. six coverage ratios,

5. two profitability ratios, and

6. two leverage ratios.

In addition, the expected value of the FCFE is quantified and the median value and the standard deviation are reported as well.

The probability distribution of the FCFE is displayed as a histogram. The x-axis and y-axis of the histogram are variable to achieve the best possible depiction. The default probability for the current period and the cumulative default probability are displayed.

The chosen confidence levels for the cash-flow-at-risk are 1%, 5%, and 10%.

The calculated coverage ratios are (1) EBIT to interest, (2) EBITDA to interest, (3) DSCR, (4) Debt payback period[18], (5) cash flow from operations (CFO) to Total Debt, and (6) FCFF to Total Debt. The coverage ratios are discussed in section 2.1.3.2.

The two reported profitability ratios are the gross profit margin, defined as the quotient of revenue minus variable costs and revenue, and the pretax return on capital, defined as the quotient of net income and the book value of equity.

As leverage ratios, the long-term debt to capitalization and the total debt to capitalization ratio are calculated. The calculation of the ratios is based on book values.

One page of the output file compiled within the case study in the fifth chapter is displayed in figure 3.3. The number of iterations for the displayed simulation was 500,000, showing the probability distribution of the cash flow after one year.

3.4   Status Quo and Limitations of the Valuation Tool

3.4.1   Status Quo

The status quo of the valuation tool is represented by a stand-alone, computer-based tool that is specified for the valuation of power plant ventures financed via project finance.

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[18]The debt payback period is defined as the quotient of total debt and the FCFE.

Figure 3.3
Output File – Cash Flow Distribution with Measures
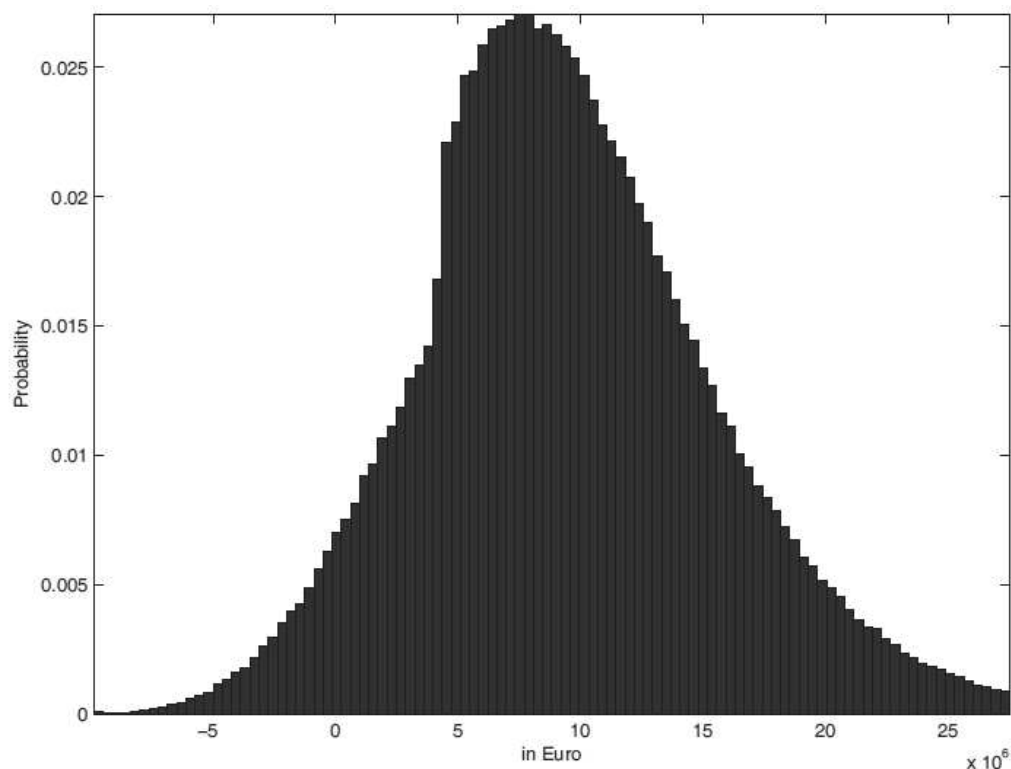
| Expected FCFE: | 9.4e+006 | Default Probability | 0.00 % |
| | | Cum Default Probability | 0.00 % |

Key Ratios

Profitability		*Cashflow at Risk*	
Gross Profit Margin:	0.00		
Pretax Return on Capital:	0.01	<=1%:	−3680548
		<=5%:	−121808
Coverage Ratios		<=10%:	1965569
EBITDA zu Zins:	6.76		
EBIT zu Zins:	5.00	*Descriptive Statistics*	
Debt Service Coverage Ratio:	6.30		
Debt Payback Period:	25.89	Median:	8827923
CFO zu Total Debt:	0.02	Std. Abw. in % des Mittelwertes:	66.41
FCFF zu Total Debt:	0.02		
Leverage Ratios			
Long–term debt/Capitalization:	0.50		
Total Debt/Capitalization:	0.50		

Source: Own work.

The main quantitative results of the valuation tool applied for the valuation of a project finance investment are:

- probability distributions of the expected future cash flows at certain points-in-time,

- a probability distribution of the expected NPV,

- cover ratios and default probabilities at certain points-in-time, and

- the cumulative default probability of the project over the entire lifespan.

Within the valuation process, the valuation tool (i) uses various advanced forecast models for the forecast of level data, volatilities, and correlations and (ii) considers correlations between all input parameters. Performed robustness checks and the results of the case study in the fifth section suggest the tool has been well specified.

The implementation of the valuation tool is made as simple as possible, in order to enable less experienced users to apply it. The relevant parameters are typed in a Microsoft Excel spreadsheet. After the start of the valuation process, the whole process is executed automatically, generating an output file with all results and a summary of the input parameters.

3.4.2 Limitations

The present limitations of the PFVT are mainly related to three aspects. First, the PFVT in its current stage is developed and calibrated for the valuation of power plant ventures. Second, the tool assumes the same discount rate over all cash flow paths. Third, hedging is not yet implemented.

The first point relates to the question whether the obtained results are of general validity. In the case study in the fifth chapter, the focus is on the results' relative robustness and not on the absolute valuation results. Hence, it would be of interest to apply the valuation tool on projects in other sectors in order to verify the accuracy of the results. Projects in the infrastructure or the telecommunication sector, for example, would be suitable. However, public data availability unfortunately is low. It is intended to obtain data from practitioners active in this field in the near future to extend the range of applications.

The application of the same discount rate, i.e. the use of the same operational risk or unlevered cost of equity, on all cash flow paths could lead to a biased estimate of the NPV. The fact that normally a higher volatility is linked to higher risk and hence higher cost of capital has to be taken into account. The theory of risk-neutral

valuation promises a solution. According to this approach, the cost of capital must be calculated separately for every cash flow path to ensure the theoretical accuracy of the valuation. The implementation of an advanced cost of capital procedure is one of the next intended improvements of the PFVT.

The implementation of hedging would allow for specifying hedging strategies within the individual valuation tasks. As hedging is a common phenomenon observed in project finance investments, as is discussed in section 2.1.1.5, the result would be a more realistic specification of a valuation task. Hedging strategies regarding the costs of input and output factors, currency rates, and interest rates could be introduced. In the case of a power plant venture, the hedging of the only output, the electricity, based on the results in chapter 4 regarding the risk premia, i.e. the bias between futures prices and the expected spot prices, is of interest. The main advantage of hedging is reducing future cash flow variability. As an implementation of hedging requires a significant reprogramming of the PFVT, hopefully the next generation of doctorate students will solve this drawback.

3.5 Excursus: Time Series Modeling and Forecasting

3.5.1 Introduction

The results of a valuation process based on stochastic cash flow modeling rely heavily on the appropriate specification of the input factors and, in particular, on the applied forecast models. The forecast models implemented within the PFVT are based on time series modeling. This excursus serves as a short introduction to this topic and aims to clarify the rationale, the advantages, and the potential drawbacks of the implemented forecast models. However, this excursus does not provide a comprehensive overview. I solely address the forecast models implemented within the PFVT and I refer the interested reader to continuative literature regarding further models.[19] Furthermore, I try to maintain a low level of mathematical complexity in this section and rather focus on the intuition behind the forecast models of interest.

A time series is generally defined as a sequence of observations (data points) chronologically ordered according to their time of occurrence. The time intervals between the single observations are typically uniform. Time series modeling refers to the analysis of historical time series with the aim of identifying their characteristics. These characteristics can then be used for the forecasting of future values. Often, the same

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[19]Cf. for example Geman (2005) and Weron (2006) for an overview on forecast models regarding commodity and electricity markets. A more detailed discussion on time series modeling and forecasting can be found, for example, in Brooks (2002) on an introductory level and in Pena et al. (2001) and Tsay (2002) in a more sophisticated context.

mathematical model is used for modeling and forecasting purposes. Therefore, in a first step, an appropriate model that describes the behavior of a time series is identified, and then, in a second step, it is used for the forecast of future time series values.

In the following I discuss forecast models for level data, volatilities, and correlations. The forecast of all these three time series characteristics is necessary in a typical valuation process. For the forecast of level data three models can be used within the PFVT: (1) the random walk (with and without drift), (2) ARMA, and (3) the mean reversion model. For the volatility forecast the implemented models are: (1) historical volatility, (2) the general autoregressive conditional heteroskedasticity (GARCH) model, (3) the GJR-GARCH model, and (4) the EGARCH model. For the correlation forecast, there are two models implemented: (1) historical correlation and (2) the dynamic conditional correlation (DCC) model.

In the next sections, following symbols are used if not differently stated: the value of a time series at time t is noted as y_t, the value of the same time series at time *t-1* as y_{t-1}. The first difference of a time series at time t is r_t. The volatility of a time series at time t is noted as σ_t.

3.5.2 Forecast Models Level Data

I introduce the random walk model with and without trend, the ARMA model class, and the mean reversion model as forecast models for level data.

Random walk model

The random walk model is part of an important class of stochastic processes[20] mainly used for the modeling of non-deterministic time series. The Brownian motion, also known in the mathematical literature as Wiener process, is the continuous-time version of the random walk.

A simple random walk is defined as

$$y_t = y_{t-1} + \mu + u_t \tag{3.1}$$

with μ as a constant drift component parameter and u_t a white noise process.

The white noise process is a standard stochastic process often applied to model random shocks in times series. White noise is defined as a stationary[21] discrete

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[20]A stochastic process can broadly be defined as a time series variable that is evolving in a random way.

[21]A time series that exhibits stationarity is characterized by the properties that the mean, variance, and autocorrelation structure are constant.

stochastic process, i.e. a process of uncorrelated random variables with an expected value of zero and with a constant volatility. A white noise process has no discernible structure. Normally, it is assumed that the white noise exhibits a normal distribution.

The general continuous notation of a change in the time series variable y as a differential equation of the generalized Wiener Process is

$$dy = adt + bdz \tag{3.2}$$

with a as a trend parameter and b as a volatility parameter.

Formula (4.2) states that the value y_t of a time series at time t equals the value one time period before plus a random change (random walk without drift). In the case that μ is unequal to zero a deterministic change is in addition applied (random walk with drift).

An important characteristic of the random walk is the fact that it follows the Markov property. This property implies that the future values do not depend on the current or past values. Thus, the expected value of a random walk without drift is its actual value. For a random walk with drift the expected value is the actual value plus the drift component times the incremental time step.

The use of the random walk is in particular popular in finance due to the market efficiency theorem and its implications. According to this theorem the evaluation of market prices, i.e. stock prices and other financial asset prices, is best described by the random walk with or without drift. Also the fundamental models in option pricing are based on the random walk.[22]

Autoregressive moving average (ARMA)

The ARMA model class consists of linear models for stationary and discrete stochastic time series. I address the general ARMA model in three steps. First, I discuss the first part of the general model class, the autoregressive (AR) models. Second, the moving average (MA) model class is introduced. Finally, the combination of these two model classes to the ARMA model class is addressed.

AR models

The basic assumption underlying AR models is the existence of a temporal relation between the values of a time series. In this case, the actual value of a time series can be to a certain degree explained by a linear function of its past values. The number

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[22]Cf. Hull (2008) for a discussion of the application of random walks in the modeling of financial data.

of past values, denoted as p, determines the order of the AR model.

An AR model of order p, abbreviated as AR (p), is noted as

$$y_t = \alpha + \sum_{i=1}^{p} a_i y_{t-i} + u_t \tag{3.3}$$

where α and the a_i are constant parameters and u_t is the white noise process discussed above.

The simplest AR model is the AR (1) model, defined as

$$y_t = \alpha + a_1 y_{t-1} + u_t. \tag{3.4}$$

The AR (1) process is a discrete version of the continuous mean reversion process discussed below.

The current value of a time series modeled with an AR model is the sum of the past weighted values of the time series, an error term, and a constant.

MA models

MA models use the past noise terms of a time series to model the future values.

An MA model of order q, abbreviated as MA (q), is defined as

$$y_t = \beta + \sum_{j=1}^{q} b_j u_{t-j} + u_t \tag{3.5}$$

with β and b_j as constant parameters.

The simplest MA model, the MA (1) model is noted as

$$y_t = \beta + b_1 u_{t-1} + u_t. \tag{3.6}$$

The MA (1) model is the random walk discussed above.

The current value of a time series modeled with the MA model class is the weighted average of the q processing noise terms and an error term.

ARMA models

The combination of the two above discussed model classes, namely the AR and MA models, results in the ARMA model class. ARMA models are linear models for

stationary time series. The general ARMA (p, q) is defined as

$$y_t = \chi + \sum_{i=1}^{p} a_i y_{t-i} + \sum_{j=1}^{q} b_j u_{t-j} + u_t \tag{3.7}$$

with χ as a constant.

The simplest ARMA model is the ARMA (1, 1) which can be noted as

$$y_t = \chi + a_1 y_{t-1} + b_1 u_{t-1} + u_t. \tag{3.8}$$

The ARMA models were introduced by Box & Jenkins (1970) in econometrics. Today, the use of the ARMA model mainly focuses on the ARMA (1, 1) model as it yields good forecast results with manageable modeling complexity.[23]

Mean reversion model

Mean reversion is a term for a stochastic process used in the financial literature which is known in the mathematical literature as the Ornstein-Uhlenbeck process. The process is a continuous stochastic process defined as

$$dy_t = \theta(\mu - y_t)dt + \sigma dW_t \tag{3.9}$$

where θ, μ, and σ are (constant) parameters and W_t being the Wiener process.

The main characteristic of the mean reversion model is already included in its name: Time series modeled with this approach tend to return to the long-term mean value represented by μ in the above equation. Θ is a rate parameter determining on which time scale the times series variable is converging towards μ.

Mean reversion is an effect often observed in economic time series. It describes the tendency of certain time series to return to their long-term average. This is of particular interest for commodities, as parts of the academic literature assume that commodity prices mean-revert to long-run equilibrium prices.[24]

Vasicek (1977) applied the Ornstein-Uhlenbeck process for financial data, introducing a one-factor model for the evaluation of interest rates to the financial literature. Since the work of Vasicek's many applications of the mean reversion characteristic for financial data have been found. Thus, this model belongs to the standard time series models applied in finance.

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[23]Cf. for example Neusser (2009) for a discussion of the parameter estimation for a general ARMA (p, q).

[24]Cf. for example Schwartz (1997) for a discussion of this assumption.

3.5.3 Forecast Models Volatility

The above discussed models regarding the mean or level assume homoscedasticity; in other words, a constant variance and covariance function is assumed.[25] However, in reality this assumption is rarely justified.[26] In this section, I introduce models that are able to deal with time-varying volatility. I discuss the historical volatility approach, the basic GARCH model, and advanced models related to the basic GARCH model, namely the GJR-GARCH and the EGARCH.

Historical volatility

The historical volatility approach consists in the forecast of the future volatility based on the past values of a time series variable. Another term for this approach is realized volatility. The historical volatility is calculated as the standard deviation of the past returns.

To calculate the historical volatility, three parameters must be specified:

1. data frequency,

2. time interval, and

3. time period.

Data frequency[27] refers to the time interval between the single observations of a time series. In general, time series have a daily, weekly, or monthly frequency.[28] The choice of the data frequency has a significant impact as the estimation results can be very sensitive to this parameter.[29] The time interval specifies the number of observations that are included in the calculation. This parameter is in particular critical when the chosen time interval is either too short or too long. In the former case the selected time period can be randomly uncharacteristic for the modeled time series. In the latter case the too long time interval can lead to a negligence of recent changes in the time series characteristics as they are averaged out with the past data. The time period is finally the period over which the standard deviation is calculated. This parameter is critical due to the fact that financial time series data are not stable, i.e. the properties of a times series – inter alia the volatility – change

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[25]Cf. Weron (2006), p. 113.

[26]Cf. Mandelbrot (1963) and Fama (1965) for first empirical results questioning the constant volatility assumption for financial data.

[27]Depending on the data frequency the volatility must be annualized. Since the variance is linear in time the volatility evolves with the square root of time.

[28]Stock prices are, for example, typically available with a daily frequency, whereas macroeconomic data are mostly available with a monthly frequency.

[29]Electricity prices are a good example due to electricity's diverse seasonality.

over time. Similar to the case of the too short time interval using a time period that is untypical for the time series of interest can also result in misleading volatility estimation.

When the historical volatility approach is in practice applied the rolling window method is often used. A fixed time interval within this method is specified for the estimation of the volatility; after the inclusion of a new observation the oldest data point is excluded. A time interval between 90 and 180 days is usually selected, based on daily data. The time period ends with the last available observation.

Advantages of the historical volatility approach are its easy application and the intuitive understandability.

GARCH

The general autoregressive conditional heteroskedasticity (GARCH) model was introduced by Tim Bollerslev in 1986. Nowadays it can be seen as the standard model for volatility modeling and forecasting, both in the academic world and in real life applications. The work of Bollerslev (1986) is based on Engle (1982) who developed the autoregressive conditional heteroskedasticity (ARCH) model.[30] In the developed valuation tool both the standard GARCH model and the extensions GJR-GARCH as well as E-GARCH are implemented. I first discuss the ARCH model before I examine the GARCH model.[31] The derivatives are discussed thereafter. An excellent survey on this topic can be found in Bollerslev et al. (1992).

ARCH models

Robert Engle introduced the ARCH process in 1982 as an approach to model the variance of a time series (Engle (1982)).[32]

An ARCH process of order one, noted as ARCH (1), is defined as

$$r_t = \sigma_t X_t \tag{3.10}$$

with

$$\sigma_t^2 = \omega_0 + \alpha_1 r_{t-1}^2 \tag{3.11}$$

---

[30]Tim Bollerslev was a doctorate student of Robert Engle.

[31]Cf. Brooks (2002) for a discussion of the parameter estimation procedures for ARCH and GARCH models.

[32]In 2003 Robert Engle received (together with Clive Granger) the Nobel Memorial Prize in Economic Sciences "for methods of analyzing economic time series with time-varying volatility (ARCH)"; Diebold (2004), p. 165.

as a process for the conditional variance. σ_t, ω_0, and α_1 are positive and constant parameters; X_t is an independent and identically-distributed random variable, i.e. white noise. It is normally assumed that X_t is standard normally distributed.

The general ARCH (p) process is defined as

$$\sigma_t^2 = \omega_0 + \alpha_1 r_{t-1}^2 + ... + \alpha_p r_{t-p}^2 = \omega_0 + \sum_{i=1}^{p} \alpha_i r_{t-i}^2. \tag{3.12}$$

The first parameter in equation (3.12) is the weighted unconditional variance

$$\omega_0 = (1 - \sum_{t=1}^{p} \alpha_t)\overline{\sigma}^2 > 0. \tag{3.13}$$

The second parameter (class) in equation (3.12), the α_t's, are constant and equal or larger than zero.

The conditional variance in the general model is a weighted sum of squared observations of the time series. It is ensured that the most recent observations are weighted more if the parameters in the sum are chosen in a certain way.

Two advantages of the ARCH model are: older information of a time series does not get lost and more present data is weighted more. Further advantages are the intuitive understanding and the relatively simple implementation. However, there are limitations of the ARCH models: the number of past values, used to estimate the variance, tends to be very high, resulting in a large and difficult to handle model. In addition, there is no clear best approach to determine the value of q. Furthermore, the non-negativity constraints might be violated.[33]

GARCH models

Tim Bollerslev introduced the GARCH model in 1986 (Bollerslev (1986)). As already implied by the name the GARCH model is a generalization of the ARCH model. The generalization is that the conditional variance depends on its own history.

Similar to above the GARCH (1, 1) model is defined as

$$\sigma_t^2 = \omega_0 + \alpha_1 r_{t-1}^2 + \beta_1 \sigma_{t-1}^2. \tag{3.14}$$

---

[33]Cf. Brooks (2002), p. 452.

The general GARCH (p, q) model is defined as

$$
\begin{aligned}
\sigma_t^2 &= \omega_0 + \alpha_1 r_{t-1}^2 + \alpha_2 r_{t-2}^2 + ... + \alpha_p r_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + \beta_2 \sigma_{t-2}^2 + ... + \beta_q \sigma_{t-q}^2 \\
&= \omega_0 + \sum_{i=1}^{p} \alpha_i r_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2.
\end{aligned}
\tag{3.15}
$$

The conditional volatility is modeled within the GARCH model as a linear combination of a constant, the sum of weighted squared past errors, and weighted past values of its own.

The generalization of the ARCH model is that in addition to the past values the estimated variance is included.

Forecast results obtained by the GARCH model are characterized by either a monotone convergence or stability. In the long term the volatility forecast converges to the conditional volatility.

The main drawback of the GARCH model is that it can not capture the asymmetric impact of negative and positive returns on the volatility. GARCH models assume that both positive and negative returns have the same effect on the volatility. However, empirical studies show that negative returns tend to indicate higher volatilities than positive. The economic rationale behind this observation is probably that negative news have a stronger impact on the market than positive news.[34]

The discussed drawback can be overcome by one of the two models introduced in the following.

EGARCH

The EGARCH model was proposed by Nelson (1991). The motivation was an overcoming of the main weakness of the GARCH model, namely its failure to capture asymmetric volatility effects.

The general EGARCH (p, q) process is defined as[35]

$$
ln(\sigma_t^2) = \omega + \beta ln(\sigma_{t-1}^2) + \gamma \frac{r_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|r_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right].
\tag{3.16}
$$

The reader is referred to the original work of Nelson (1991) for a discussion of the individual parameters.

Besides the model's advantage to capture the asymmetries, the fact that the con-

---

[34]In the case of stock returns, this effect is called *leverage effect* and was introduced by Black (1976*b*) to the financial literature.

[35]Cf. Brooks (2002), p. 470.

ditional variance is modeled logarithmically causes the improvement that no non-negativity constraints on the model parameters must be imposed.

GJR-GARCH

Glosten, Jagannathan, and Runkle developed an extension of the GARCH model which accounts for possible asymmetries (Glosten et al. (1993)). The model is named after the authors as GJR model or GJR-GARCH model.

Within this model the negative and positive returns are separately estimated to capture the asymmetric effects. The proposed model contains a dummy variable which is defined as

$$I_{t-1} = \begin{cases} 1 & \text{if } r_{t-1} < 0 \\ 0 & \text{otherwise} \end{cases} \tag{3.17}$$

The GJR-GARCH model is noted as[36]

$$\sigma_t^2 = \omega 0 + \alpha_1 r_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma r_{t-1}^2 I_{t-1}. \tag{3.18}$$

The reader is again referred to the original work of Glosten et al. (1993) for a discussion of the individual parameters.

The GJR-GARCH model extends the GARCH model at one additional term which accounts for the asymmetries.

3.5.4 Forecast Models Correlation

Correlation is a measure of linear relationships between two or more time series or random variables.[37] An appropriate estimation of the correlation structure within the input parameters in the valuation process is of immense importance for the specification of a realistic valuation task.[38] I discuss and implement two common forecast

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[36]Cf. Brooks (2002), p. 469.

[37]To be more precise, it is the correlation coefficient that is a quantitative measure for the linear relationship. The Pearson correlation coefficient $\rho_{X,Y}$ for two random variables X and Y defined as

$$\rho_{X,Y} = \frac{E[(X - E(X))(Y - E(Y))]}{\sigma_X \sigma_Y}$$

is mostly used. σ_X and σ_Y are the standard deviations of X and Y, respectively. E is the expectation operator.

[38]The PFVT is intended to be mainly applied in the context of energy projects. A good example for the impact of correlations on the valuation results is a project where both oil as well as gas are an input or an output factor. In the past, it was common to couple the gas price on the oil price, i.e. a strong positive correlation between these two time series was apparent. A negligence or misspecification of the correlation between these two commodities can hence result in valuation

models, the historical correlation approach and the DCC model.

Historical correlation

The historical correlation approach is similar to the above discussed historical volatility approach. Based on two historical time series the correlation coefficient is estimated within this approach. The obtained correlation coefficient is then used as a forecast for the future correlation.

The correlation coefficient is estimated based on stationary time series. Thus, the first difference of financial time series is used for the estimation, e.g. the return time series instead of the stock price time series is relevant. The obtained estimator for the correlation is a point estimate. All past observations included in the estimation procedure are equally weighted.

Analog to the historical volatility approach the estimation result is sensitive to the three above discussed parameters, namely (1) the data frequency, (2) the time interval, and (3) the time period. I refer to the section about the historical volatility approach for a discussion of the parameters and their impact on the estimation results. I only emphasize that in the case of correlations the time instability of financial time series parameters is even more critical. The rolling window method is also often used in the application of the historical correlation method.[39]

The use of the historical correlation approach is common in real life applications, in particular for long-term forecasts. A drawback of the approach is its limitation to only two time series.

Dynamic Conditional Correlation

The DCC model was introduced in 2001 by Engle and Sheppard.[40] The DCC model is a multivariate GARCH model, i.e. a non-linear combination of univariate GARCH models. The model aims to estimate the correlation dynamically. The specification of the model enables the simultaneous estimation of the correlation between arbitrary many time series.[41]

The correlation estimation via the DCC model is a two step procedure. In a first step, the parameters of a univariate GARCH model for every time series included

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results that are completely unrealistic due to the coupling.

[39] Cf. the previous section for a discussion of the rolling window method.

[40] Cf. the working paper of Engle & Sheppard (2001) for an introduction of the DCC. The model was finally published in the *Journal of Business and Economics Statistics* in 2002 by Engle; cf. Engle (2002).

[41] The Constant Conditional Correlation (CCC) model proposed by Bollerslev in 1990 can be seen as the ancestor of the DCC model. It is also based on a similar parameter estimation procedure. However, the model assumes constant correlation.

in the estimation procedure are estimated separately. Standardized errors based on the estimation results are then calculated. In a second step, the correlations are estimated based on the standardized errors.

I forgo to provide a mathematical definition of the DCC model as it would go beyond the scope of this dissertation. The interested reader is referred to the original publication of Engle (2002) as well as to the excellent survey of Bauwens et al. (2006).

Similar to the volatility forecasts performed via a GARCH model correlation forecasts performed by the DCC models tend to be either stable or to converge to the long-term average of the time series. Thus, in the long term the results are identical to the results obtained by the historical correlation approach. On average the convergence takes place between a few weeks and a few months.

Advantages of the DCC model are its appropriateness for financial data as it captures its characteristics and the ability to model the correlation dynamically. The correlation is dependent on the standardized returns and on its past. A drawback, in particular from this dissertation's point of view, is the fact that in the long term the results of the DCC converge to the results of the simple historical correlation method. This poses the question whether the high complexity of the DCC model justifies its application since the parameter estimation is difficult and data-intensive.

3.6 Concluding Remarks and Future Research

The newly developed project finance valuation tool is introduced in this chapter. The tool is based on stochastic cash flow modeling and advanced forecast models. This tool has been developed for the valuation of project finance investments and will be used for the valuation of a power plant venture in the fifth chapter.

The tool valuates project finance investments from the perspective both of an equity and a debt provider. The tool uses various forecast models for the separate input and output factors, i.e. level data, volatilities, and correlations, and combines these factors on the basis of on a predefined cash flow equation. Then a predefined number of future cash flow paths is simulated; these paths are aggregated to probability distributions of the expected cash flows. The probability distribution of the expected NPV is computed based on these distributions. Besides that, the cumulative default probability over the project's lifespan is derived as one of the main results of the valuation process.

The main results are probability distributions of the expected NPV, expected future cash flows, and the cumulative default probability over the lifetime of the project.

The tool in its current stage is a valuation tool for single projects. As this is not

a limitation for the questions posed in this dissertation, it is of interest to extend the valuation tool to the application in the context of a portfolio of projects in the future. In particular in the case of power plant ventures, the examination of whole power plant fleets is of interest.

The implementation of further forecast models such as futures-based models for volatility forecasts is also intended. This model class allows the introduction of recent market expectations in the valuation process. Therefore, the actual market expectations are taken into account and the valuation results may become more realistic. In addition, hedging needs to be implemented to obtain even more realistic results.

Furthermore, an extension of the valuation tool for real options[42] seems to be interesting and promising. The NPV method is based, among others, on the assumption that future actions are already determined at the beginning of a project. Real options analysis abandons this assumption and allows for future flexibility.[43] Thus, a real option is defined as "the right, but not the obligation, to take an action (e.g., deferring, expanding, contracting, or abandoning) at a predetermined cost called the exercise price, for a predetermined period of time – the life of the option".[44] Already in 2001, as reported in the survey of Graham & Harvey (2001), 27% of the participants answered that they (always or mostly) apply real options when valuing important capital investments. It can be assumed that this number continues to grow, as the advantage of the real options analysis is apparent from a theoretical point of view. In particular for energy projects, where future flexibility plays a major role, real options have the power to significantly increase the insight into the project. Thus, it is intended to implement real options into the valuation tool as soon as practicable.

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[42]Cf. for example Dixit & Pindyck (1994) and Copeland & Antikarov (2001) for profound introductory literature on real options.

[43]Cf. Erner et al. (2003) for a discussion of the advantages of the real options approach compared with the traditional valuation approach based on the NPV.

[44]Copeland & Antikarov (2001), p. 5.

Chapter 4

Price Formation in the German Electricity Wholesale Market – An Empirical Analysis

According to the theoretical and empirical literature the risk premia approach seems to be the most promising theoretical foundation for price formation in electricity futures markets. As the commodity electricity is non-storable, all electricity contracts are forward contracts. In particular the exchange-traded day-ahead market contracts, which are commonly termed as spot contracts, are consequently future contracts with a time-to-delivery of one day.

In this chapter I conduct an empirical analysis of the German electricity wholesale market. I aim to determine whether there is evidence for the risk premia approach being an appropriate price formation mechanism. I analyze and report the obtained results for the spot and futures market separately. Regarding the spot market I analyze all three market segments: the block contract market, the day-ahead market, and the intraday market. These market segments were or are in operation since the foundation of the German wholesale market in its current form in 2002. At the beginning, I discuss the underlying research question, the data, and the applied methodology. Then, I address the liquidity of the individual market segments. Afterwards, I report descriptive statistics for the spot and the futures market, and analyze the existence of seasonality in the price time series and the occurrence of negative prices in the spot market. I conclude the chapter with a summary of the results regarding the risk premia in spot and futures contracts and an outline of promising avenues for future research.

This chapter aims to answer the following three key questions:

- Is there evidence for the suitability of the risk premia approach as theoretical price formation mechanism in the German electricity market?

- Specifically, is there empirical evidence for existence of risk premia in the German electricity market?

- In the case of empirical evidence for risk premia, what are the properties of these risk premia and is it possible to identify potential drivers?

4.1 Research Question

Theoretical and empirical literature identify the risk premia approach as the most promising theoretical foundation of price formation in electricity future markets.[1] The following analysis of the German electricity wholesale market is related to that literature. I focus on the empirical verification of the risk premia approach for the German market. The research question in this chapter is whether there is evidence for the suitability of the risk premia approach as a price formation mechanism for the German electricity market. Thus, the focus of the analysis is on empirical evidence for risk premia in the exchange-traded electricity contracts.[2]

Empirical evidence for the adequacy of the risk premia approach is found for other electricity wholesale markets. Similar findings for the German market would imply that it exhibits characteristics parallel to these markets. Furthermore, these findings would imply that the observed electricity prices are biased estimators of the expected future spot price.

I conduct an in-depth empirical analysis of the German electricity market, analyzing all market segments[3] that are or were active in the last eight years. I divide this analysis into two parts. The first part deals with the spot market, and the second part with the futures market.[4] I analyze the risk premia from an ex post perspective. An analysis from this point of view relies on the assumption that the market participants

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[1]Cf. section 2.3 for a discussion of the theory behind price formation in electricity futures markets and of the empirical evidence.

[2]Cf. Schnorrenberg (2006) for a first analysis of price formation in the German forward market and for a discussion of other potential price formation mechanisms.

[3]The options market is not considered in the following analysis of the German electricity wholesale market due to the observed low liquidity. Furthermore, the focus of the analysis is on price formation in electricity futures markets. The liquidity in the options market has been low since the beginning and no real improvement is observed over the years. In 2009, for example, trading in the options market took only place on 30 of 252 trading days.

[4]Cf. also Pietz (2009a) for results regarding the German futures market and Pietz (2009b) for results regarding the German spot market.

form their forecasts based on rational expectations.[5] This assumption ensures that the ex post risk premia are on average equal to the ex ante risk premia.[6]

Regarding the German spot market, the research of this dissertation is related to the work of Ronn & Wimschulte (2009) and of Viehmann (2009). Ronn & Wimschulte (2009) conduct to my best knowledge the first empirical analysis of the block contract market located at the EEX; Viehmann (2009) conducts to my best knowledge the first empirical analysis of the day-ahead market located at the EEX. In the following, I confirm the results obtained for the block contract market; I find similar results for the day-ahead market. However, I take another point of view from Viehmann (2009) who uses the day-ahead market prices as spot prices in relation to OTC prices.[7] I estimate the risk premia in the day-ahead market contracts in relation to the intraday market contracts; thus the day-ahead market is regarded as the futures market. By extending the sample period as well as by including the intraday market in this analysis I am also able to answer additional questions regarding the German spot market.

Previous research regarding the German futures market has been conducted by Wilkens & Wimschulte (2007). The authors use data ranging from 2002 to 2004 and find evidence for positive risk premia in the German futures market. I extend this research by using a larger dataset, spanning almost eight years. The data are hence characterized by a higher level of market liquidity and a more mature market environment, which is expected to lead to more meaningful and robust results.

I contribute with my research in at least a threefold way to the existing literature. First, to my best knowledge, I am the first to conduct an in-depth analysis of the German intraday market. By analyzing a sample period covering 30 months, I believe that first empirical conclusions can be drawn.[8] Second, the sample period in which all three market segments of the German spot market were simultaneously existent gives me a unique opportunity to investigate the existence of a term structure of risk premia on a very short time scale. Third, through the analysis of the German futures market, I am able to contribute to and to extend the empirical literature and the ongoing discussion on the magnitude and on the sign of potential risk premia in electricity future contracts and on the evolution of these risk premia over time.

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[5]Cf. section 4.3 for a critical discussion of this assumption.

[6]Cf. section 4.3 for a discussion of the applied methodology.

[7]Viehmann (2009) uses price data from the Austrian exchange as proxies for OTC prices regarding electricity delivery in Germany; cf. section 2.3.3.2 for a discussion of his methodology.

[8]Trading in the intraday market started in September 2006. However, I exclude the first 16 months of trading due to the low liquidity; cf. section 4.4.1.1 for an analysis of market liquidity.

4.2 Data

I use price and volume data from the German electricity wholesale market spanning a time period between January 2002 and June 2010. Data from the day-ahead market, the intraday market, the block contract market, and the futures market are available. All data have been directly obtained from the EEX.[9]

The day-ahead market data consist of hourly prices and the corresponding traded volume, covering the period between July 1, 2002, and June 30, 2010. Prices for the day-ahead market and all other market segments are quoted in Euro/MWh. To simplify the terminology I will report prices in Euro only. The term *hour 1* and *hour 1 contract* is used for the hour contract with delivery between midnight and 1 am; the following hour contracts are termed accordingly. The data for the day-ahead market are available 365 days a year. The daily and monthly Phelix Base and Phelix Peak[10] are already computed by the EEX; they are included in the original dataset.

Data from the block contract market are available between August 1, 2002 and August 31, 2008. The last day of the dataset is at the same time the closing day of this market segment. The dataset includes price series of the three block contracts traded in this market segment (base load, peak load, and weekend base load) and the traded volume. Each price time series consists of volume-weighted average prices.[11]

Data from the intraday market are available for the period September 25, 2006 to June 30, 2010. The first day of the dataset is at the same time the first day of trading in this market segment. The dataset includes hourly prices and the corresponding traded volume. Two prices are available for every hour contract in the intraday market, the average price and the last price. The average price is the average of all prices from trades which took place in a specific hour contract over its trading period.[12] The last price is the one at which the last trade took place. No information on the point-in-time of the individual trades is available. I discuss the question which of the time series should be used for the empirical analysis in section 4.4.2.1.

The futures market data cover the period between July 1, 2002, and June 30, 2010. Price data for the month, quarter, and year futures are available. In addition, starting March 24, 2010, data for the newly introduced week futures are available, but not included in the dataset on account of the short sample period. The futures market data consist of daily prices. In addition to the price data, the open interest and the traded volume for every future are included in the dataset. The volume

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[9]Parts of the data are not publicly available. A temporary access to the server of the EEX has to be purchased to obtain these data.

[10]Cf. section 2.2.4.2 for details regarding the calculation of the Phelix.

[11]Cf. EEX (2009*b*), p. 7.

[12]Cf. section 2.2.4.3 for a discussion of the trading process in the intraday market.

Table 4.1
Summary Data

Summary of the analyzed data. The spot market data consist of price and volume data for three market segments, namely the day-ahead market, the intraday market, and the block contract market.

	Market Segment	Data
SPOT MARKET	**Day-ahead Market**	July 1, 2002 - June 30, 2010
		Price and Traded Volume Data for every Hour Contract
		Data for all Calender Days
	Block Contract Market	August 1, 2002 - August 31, 2008
		Daily Price and Traded Volume Data
		(three block contracts: base load, peak load, weekend base load)
		Data for all Exchange Days
	Intraday Market	September 25, 2006 - June 30, 2010
		Price and Traded Volume Data for every Hour Contract
		Data for all Calender Days
FUTURES MARKET	**Futures Market**	July 1, 2002 - June 30, 2010
		Daily Price and Traded Volume Data (month, quarter, year futures)
		Daily Open Interest Data
		Data for all Exchange Days

Source: Own work.

data are also available for OTC trades which are cleared by the EEX. Only futures with financial settlement are included in the dataset as the liquidity of futures with physical settlement is very low.

Table 4.1 summarizes the data and its main characteristics. In section 4.4.1 the liquidity of the individual market segments is discussed and the choice of the data used for the empirical analysis explained.

4.3 Methodology

A definition of the risk premium requires the specification of a temporal perspective. This leads to two different, necessarily to distinguish, definitions. The first is known as the ex ante or expected risk premium, and the second as the ex post or realized risk premium.

To define the risk premium I will use the following notation in this dissertation: π stands for the risk premium, $S(t)$ for the spot price at time t, and $F(t,T)$ for the futures price at time t for a future with delivery in T.[13] E_t equals the expectation

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[13]Please note that T is in the case of electricity futures always a time period rather than a point-in-time.

operator at time t. Only information that is available up to this time is included in the expectations.

The ex ante or expected risk premium $\pi(t,T)$ at time t in a future $F(t,\ T)$ with delivery in T is defined as

$$\pi(t,T) = F(t,T) - E_t[S(T)]. \tag{4.1}$$

The second part of the right side of equation (4.1), the unobservable expected future spot price, $E_t[S(T)]$, is of critical importance for the estimation of the ex ante risk premium. Empirical research on the ex ante risk premium always requires a specification of a spot price forecast model to estimate the expected spot price. The choice of an appropriate spot price model is essential for the estimation of the ex ante risk premium. However, spot price models are very sensitive to the specific underlying assumptions.[14] Thus, consistent and robust results for the ex ante risk premium are difficult to obtain. Consequently, the focus of the empirical literature is on the ex post risk premium.

The ex post or realized risk premium $\pi(T)$ is defined as

$$\pi(T) = F(t,T) - S(T). \tag{4.2}$$

The notation of the risk premium in equation (4.2) signals that the observation takes place at maturity of the future in T. The main advantage of this definition is the availability of all relevant data in the estimation procedure.

Definition (4.1) and (4.2) can be linked through equalizing. This results in

$$\pi(t,T) - S(T) = F(t,T) - E_t[S(T)] - S(T). \tag{4.3}$$

Under the assumption that market participants form their forecasts based on rational expectations[15], equation (4.3) can be written as

$$F(t,T) - S(T) = \pi(t,T) + \epsilon_t. \tag{4.4}$$

According to equation (4.4), the ex post risk premium equals the ex ante risk premium plus a noise term. As the market participants form their expectations ratio-

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[14]Cf. Karakatsani & Bunn (2005) for a discussion of the difficulties regarding the application of spot price models.

[15]The assumption of rational expectations implies that (i) expectations are unbiased, i.e. the forecast error equals zero: $E(\epsilon_t) = 0$, (ii) forecast errors are uncorrelated, i.e. forecast errors in the past contain no information regarding an improvement of the forecast, and (iii) expectations are complete, i.e. the forecast cannot be improved based on the present information; cf. Schnorrenberg (2006), pp. 157-158.

nally, it is assumed that the resulting average forecast error is zero.[16]

The assumption of an average forecast error of zero is strong. In particular for a young market with a low number of market participants trading a commodity such as electricity with all its special characteristics. Thus, it has to be noted that an interpretation of the ex post risk premia is always problematic because of this assumption.

A direct implication of this assumption is the question whether a certain group of market participants possesses superior forecasting abilities. Within the applied methodology the estimated risk premia equal the profit of either the long or short side in the market. Superior forecasting abilities would result in a mix of the profitability; the risk premia would not be directly distinguishable from forecast profits and the results from an ex post risk premia analysis would be biased. It is even possible that the estimated profits are completely the result of superior forecasting ability and not of the earning of risk premia. Parts of the academic literature find support for superior forecasting abilities, at least in certain markets.[17] However, in accordance with the broad literature I presume that the assumption of rational expectations holds and hence no superior forecast profits occur.

Bryant et al. (2006) conclude the assumptions and problems underlying an empirical analysis of risk premia in futures markets concisely by stating the following:

> *In summary, risk premiums that may exist in futures market cannot be observed, because the expected future cash price cannot be observed. The standard empirical practice then is to check for speculative profits, which would be consistent with the existence of risk premiums. If speculative profit exist (the evidence on this is mixed), they must be decomposed into profits due to forecasting ability, which is also unobserved, and any residual profits. The existence of residual profits is interpreted as evidence that risk premiums are present. These premiums may be due to systematic risk if futures price changes are correlated with returns to total wealth. After adjusting "observed" risk premiums for systematic risk, it is then inferred that any residual risk premium that is not due to systematic risk may be due to hedging pressure, if measures of these two phenomena are correlated. The path by which a researcher might find*

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[16]Cf. section 2.3.2.2 for a discussion of potential interpretations of the ex post risk premium.

[17]Chang (1985) examines the profits to speculators in wheat, corn, and soybeans futures markets. The author finds evidence that large wheat speculators seem to possess some superior forecasting ability over the period 1951 to 1980. Their profits are hence the sum of a risk premium and a reward for their forecasting abilities. However, Chang (1985) makes no attempt to quantify the relative size of the two components. Leuthold et al. (1994) analyze the frozen pork bellies market on the Chicago Mercantile Exchange. When analyzing a dataset from 1982 to 1990 with daily trading activities the authors find evidence that a group of traders seems to be able to generate superior price forecasts.

evidence consistent with the generalized theory of normal backwardation is so convoluted it is littler wonder that no consensus may been reached.[18]

For empirical purposes I will calculate the ex post risk premium as

$$\pi(T) = \frac{1}{T} \sum_{t=1}^{T} (F(t,T) - S(T)). \tag{4.5}$$

The spot price *S(T)* in equation (4.5) is calculated as the average of the hourly prices during the delivery period

$$S(T) = \frac{1}{n} \sum_{i=1}^{n} S_i(t) \tag{4.6}$$

with n being the number of hours during the delivery period.

In addition I calculate a relative risk premium, π_{rel}, defined as

$$\pi_{rel}(T) = \frac{1}{T} \sum_{t=1}^{T} \left(\frac{F(t,T) - S(T)}{F(t,T)} \right). \tag{4.7}$$

The relative risk premium can be interpreted as the percentage of the futures price which is paid due to hedging purposes.

4.4 Empirical Results

4.4.1 Market Liquidity

Considering exchange-trading, market liquidity is always a critical issue, in particular in newly deregulated markets as the electricity market. Together with transaction costs and transparency standards liquidity is usually used as a measure for the functioning of an exchange.[19] Furthermore, a public discussion on the efficiency of the trading process has accompanied electricity exchanges since the beginning. A high level of liquidity (together with a high number of market participants) is of course the best argument to face this discussion.

4.4.1.1 Liquidity Spot Market

In 2009 the traded volume in the spot market amounted to 203 TWh. Similar to other electricity exchanges most of the traded volume in the spot market is observed in

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[18]Bryant et al. (2006), p. 1043.
[19]Cf. Wawer (2007), p. 25.

Figure 4.1
Traded Volume Spot Market 2003-2009

Traded volume in the spot market over the period 2003 to 2009. All market segments of the intraday market are included.
In 2009 for the first time electricity with delivery in the French market area is included in the statistic.
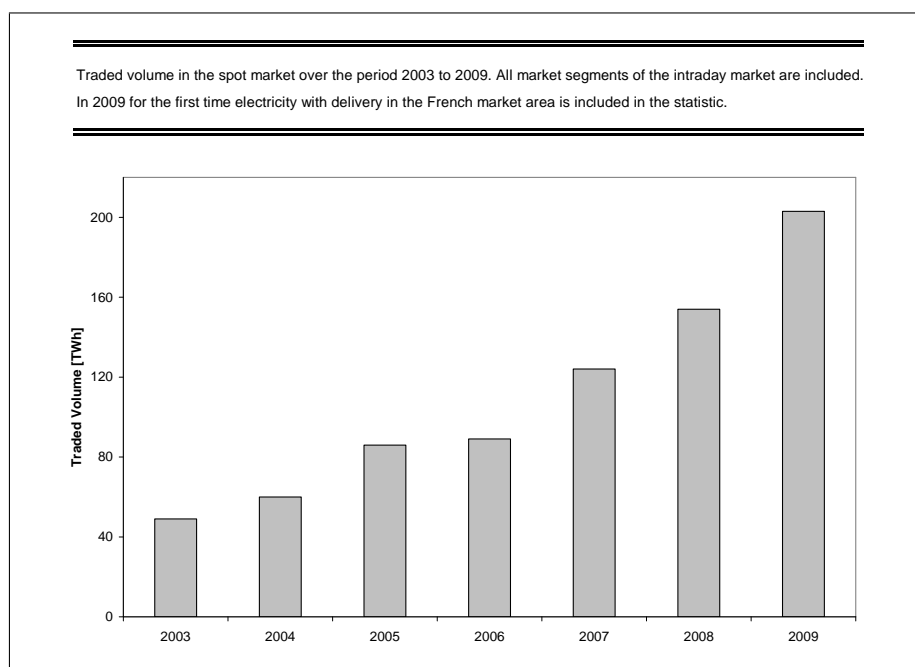
Source: Own work.

the day-ahead market. Regarding the electricity traded for delivery in Germany, the traded volume in the day-ahead market was around 136 TWh. In the intraday market approximately 6 TWh were traded. This relatively low liquidity in the intraday market could be due to the fact that this market segment is mainly used as a balance market for short-term adjustments.[20] The evolution of the traded volume in the spot market over the period 2003 to 2009 is depicted in figure 4.1.

A steady increase in the traded volume over the last years is observed. However, the increase in traded volume in 2009 appears surprising against the background of the economic crisis and the development in the futures market discussed below. However, it can easily be explained by the fact that traded electricity for delivery in France was counted for the first time in this year. This volume amounted to 53.6 TWh in 2009.[21] Without this effect a slight decline in the traded volume would have been observed.

From the beginning of the sample period the liquidity in the day-ahead market was relatively high and has steadily developed over the last years. Regarding the traded volume in the individual contracts a significantly higher volume is observed in the peak hours on working days. On non-working days no clear daily structure – except

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[20]Cf. Weber (2010), p. 3.
[21]Cf. EEX (2010*b*), p. 5.

Figure 4.2
Daily Number Contracts without Trading in the Intraday Market
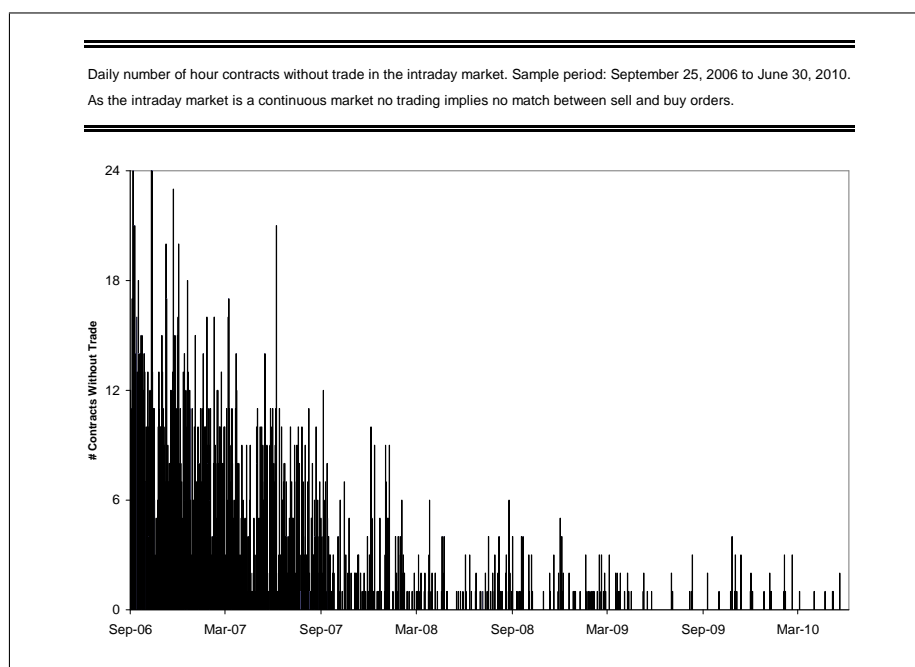
Source: Own work.

a light peak in the morning hours – is observed.

When examining the period in which the block contract market was active the volume in this submarket was relatively low. In 2006 and 2007, for example, the traded volume was 0.86 TWh and 0.61 TWh, respectively. It stands out that on approximately 30% of all days no trading took place in the block contract market. On non-working days this number was even higher. In particular the peak contract with delivery on non-working days has almost never been traded.

Trading in the intraday market started in September 2006. However, it took almost one year until the liquidity reached a sufficient level. Not only a low total volume but also a high number of hour contracts without trading, as displayed in figure 4.2, is observed in particular in the first year of operation.

For the empirical analysis of the spot market in this chapter, I restrict the available data for the spot market as follows: The day-ahead market dataset which is used for the spot market analysis starts August 1, 2002 as the EEX changed the trading system that day. The same applies to the block contract market data. However, regarding the analysis of the futures market in section 4.4.2.2 I also use the July 2002 data from the day-ahead market to obtain one additional complete future price time series, i.e. risk premia time series. I exclude the peak contract from the block

Figure 4.3
Traded Volume Futures and Forward Market 2003-2009
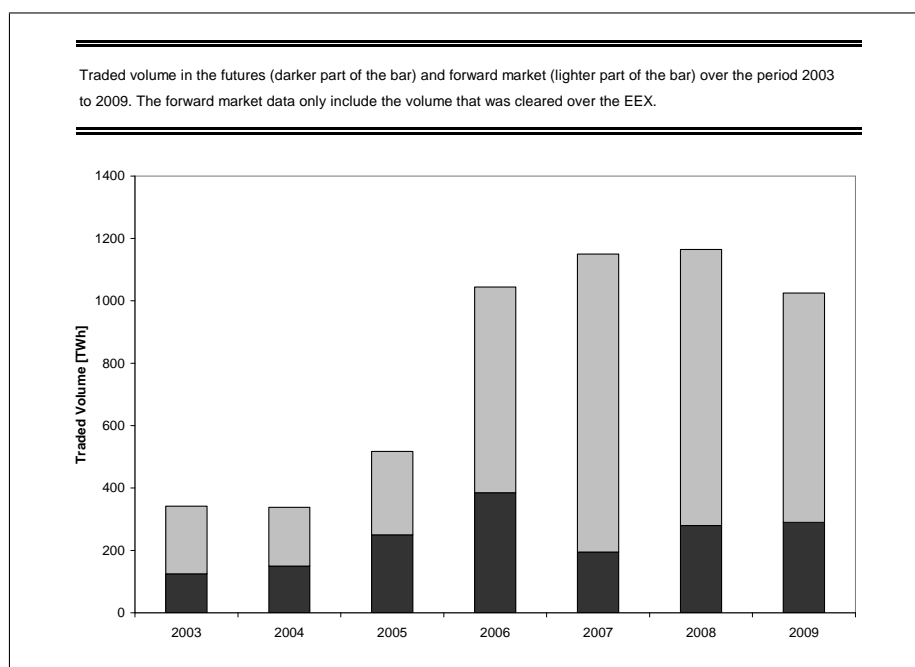
Source: Own work.

contract market due to its low liquidity. For the intraday market I decide to skip the first 15 months of trading due to the low liquidity. This decision is in particular based on the high number of hour contracts without trade over this period. Furthermore, I assume that 15 months are a necessary time period to gain market knowledge by the market participants. Thus, the first day of interest for the analysis of the intraday market is January 1, 2008.

4.4.1.2 Liquidity Futures Market

The total traded volume in the futures market and forward market, as far as the OTC trades were cleared by the EEX, was 1025 TWh in 2009. 740 TWh or approximately 72% of this volume is observed in the forward market and 285 TWh in the futures market.[22] Figure 4.3 contains the evolution of the traded volume in the futures and in the forward market over the last seven years.

The bar's dark part in figure 4.3 reflects the exchange-traded volume, the light part the volume observed in OTC clearing. As can be seen a volume decrease of around 10% is observed in 2009 due to the financial and economic crisis that erupted in 2008.

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[22]Cf. EEX (2010*b*), p. 13.

Figure 4.4

Number Traded Month Futures with Respect to Time-to-Delivery

Average number of daily traded contracts with respect to time-to-delivery. The month futures are synchronized according to the delivery month. The straight line represents the month base futures, the dashed line the month peak futures.
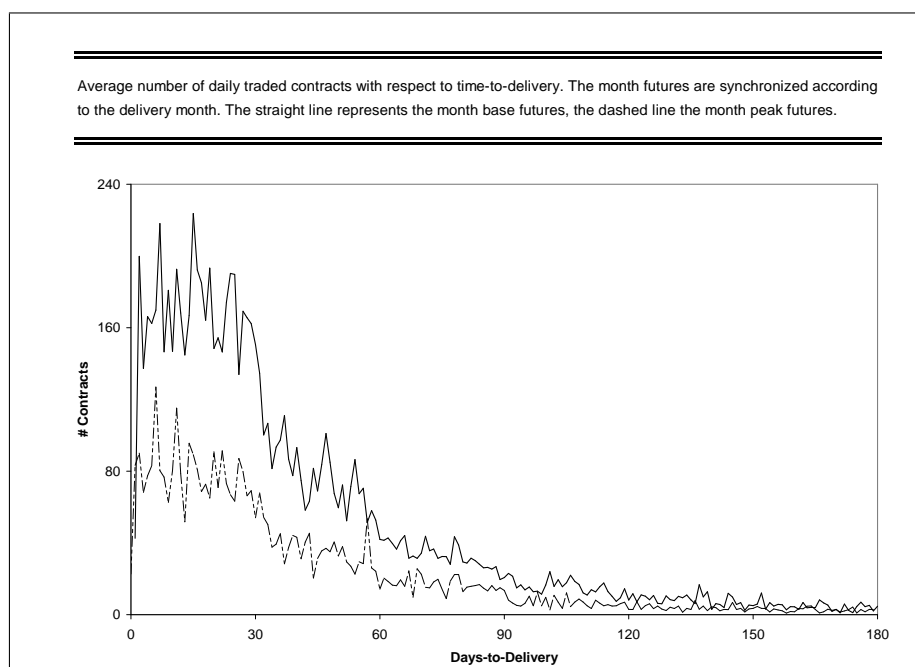
Source: Own work, based on Pietz (2009*a*).

Taking a closer look at the open interest, in the fourth quarter of 2002 the daily open interest in all futures contracts averaged to approximately 29 TWh. At the end of the sample period, the second quarter of 2010, an average open interest of 530 TWh is observed. This represents an astonishing increase in the open interest in the magnitude of a factor 18 in eight years and speaks for a liquid and a well developing market. The increase in the open interest was smooth and took place along with an increasing number of market participants, and of traded contracts.

Futures tradable at the beginning of the sample period were: a month future with delivery during the trading month, month futures with a time-to-delivery of up to six months, quarter futures for the next seven quarters, and year futures for the next three years. To extend the term structure over the past years new futures were introduced by the EEX .

When analyzing the number of traded contracts a typical pattern for futures markets is observed. Trading mainly takes place in futures with a short time-to-delivery. The average daily number of traded contracts in the month futures, both base and peak, over the whole sample period is depicted in figure 4.4.

The highest liquidity is observed in the futures with a short time-to-delivery. This

is a feature which is shared with other commodity futures markets.[23] Furthermore, figure 4.4 reveals the low liquidity of month futures with a time-to-delivery longer than three months. The same is observed for futures with a longer time-to-delivery, i.e. quarter and year futures. Consequently, the question on the reliability of these futures prices arises, as the regular trading in a futures contract appears to be a necessary condition to ensure meaningful price information. However, I recall that arbitrage opportunities align some of the futures prices and that prices for non traded futures are determined by the EEX.[24]

Table 4.2 illustrates the importance of the setting of prices by the EEX for month futures. As already indicated by figure 4.4, the percentage of days without trading is significant for the month futures with a longer time-to-delivery. Moreover, the liquidity of the peak futures seems to be significantly lower than the liquidity of the month futures. However, the high percentage of days without trading in the month futures with a longer time-to-delivery, in particular the five and six month future[25], not necessarily implies factious prices as the arbitrage relation to the quarter futures secures a pricing around the 'fair' market value.

For the empirical analysis of the futures market in this chapter, I restrict the available data for the futures market as follows: I decide to only analyze the month futures as the liquidity of futures with a longer time-to-delivery appears as too low. Furthermore, I exclude the data of the month futures during the delivery month; the reasoning for this is explained in section 4.4.2.2.

4.4.2   Descriptive Results

4.4.2.1   Spot Market

In the following I report the descriptive statistics for the three market segments of the spot market – the day-ahead market, the intraday market, and the former block contract market – separately. I focus on the day-ahead market as it is the market segment with the highest liquidity. In addition, it is the market segment which serves as underlying for the futures market and as a reference market for the whole German electricity market.

Day-Ahead Market

To obtain a first impression of the day-ahead market data, I display the daily price

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[23]Cf. Geman (2005), p. 20.

[24]Cf. section 2.2.4.3 for a discussion of the price determination process for futures without trading on a certain day.

[25]Cf. section 4.4.2.2 for a discussion of the terminology.

Table 4.2

Percentage Days without Trading in Month Futures by Year

Percentage of days without trading in the month futures. All days between August 1, 2002 and June 30, 2010 are included. Both the month base (first table) and peak (second table) future are analyzed. Values in %.

Month Base

Future	2002	2003	2004	2005	2006	2007	2008	2009	2010
One	19.05	19.84	14.12	5.88	3.97	2.00	1.98	2.77	2.38
Two	40.95	32.94	45.88	26.27	17.46	8.80	18.25	10.67	8.73
Three	48.57	49.60	65.88	51.76	36.11	22.00	36.11	37.15	18.25
Four	65.71	70.63	81.57	75.69	55.56	49.20	54.37	64.03	33.33
Five	90.48	82.14	86.27	78.82	71.83	69.60	64.29	77.87	51.59
Six	95.24	94.84	93.73	85.88	82.94	80.40	76.59	84.98	59.52

Month Peak

Future	2002	2003	2004	2005	2006	2007	2008	2009	2010
One	33.33	41.27	21.57	15.29	20.63	13.60	18.25	13.83	11.90
Two	56.19	57.54	40.39	38.82	42.06	31.60	42.06	39.92	34.13
Three	64.76	73.81	64.31	57.25	57.14	58.80	59.13	67.98	49.21
Four	92.38	88.49	80.39	78.04	75.00	77.20	81.75	81.42	61.11
Five	100.00	94.84	88.63	78.82	82.94	86.80	85.32	91.30	80.95
Six	100.00	98.02	92.94	85.88	85.32	91.20	92.06	95.65	88.10

Source: Own work.

during the sample period in figure 4.5. The daily price is calculated as the arithmetic average of the 24 hourly prices; the EEX publishes this price as the daily Phelix Base.

In addition, to illustrate the stylized facts of electricity prices discussed in section 2.2.2.1, the absolute daily (logarithmic) returns of the time series shown above are depicted in figure 4.6.

Figures 4.5 and 4.6 reveal the high volatility of the daily day-ahead market prices. Moreover, the discussed frequent price spikes are clearly observed in the price time series. The highest daily price is observed on July 27, 2006 with 301.54 Euro. July 2006 was a month with persistent high temperatures which resulted in a high power demand and a lower power plant output due to high river temperatures.[26] Furthermore, the illustration of the daily absolute returns in figure 4.6 allows the identification of volatility clusters, a common observation in financial markets.

A near examination of the time series in figure 4.5 leads to the observation of two negative daily prices at the end of the sample period. This is surprising as the day-ahead market is by far the market segment with the highest liquidity. In addition, the first occurrence of daily negative prices takes place after eight years of trading. However, this has to be seen against the background of at least three developments. First,

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[26]Cf. Viehmann (2009), p. 7.

Figure 4.5
Daily Prices Day-Ahead Market

Time series of daily prices on the day-ahead market. Sample period: August 1, 2002 to June 30, 2010. Both working and non-working days are included. The daily price is calculated as an arithmetic average of the 24 hourly prices.
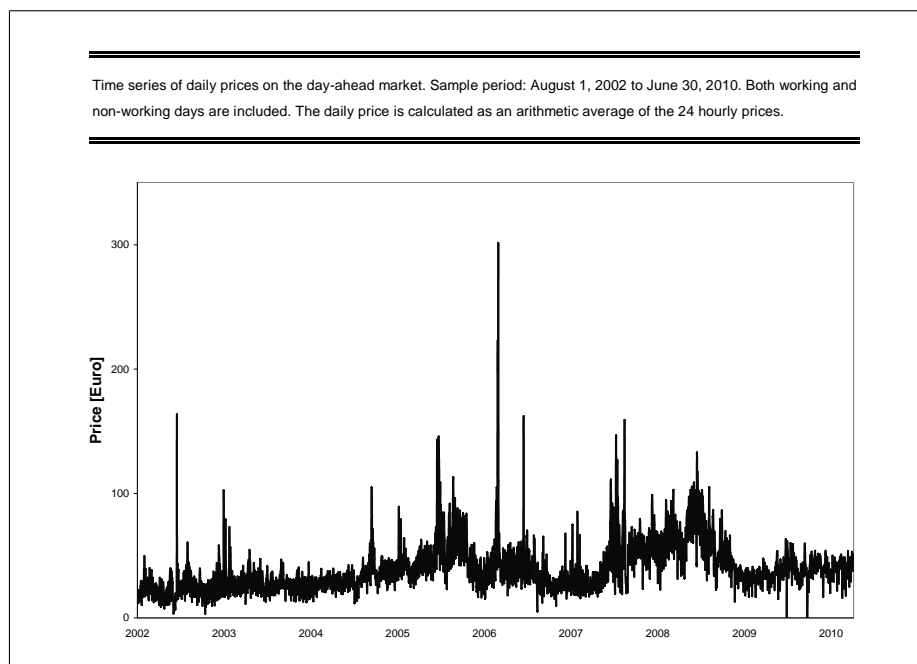
Source: Own work, based on Pietz (2009*b*).

Figure 4.6
Daily Absolute Returns Day-Ahead Market

Time series of daily absolute returns on the day-ahead market. Sample period: August 2, 2002 to June 30, 2010. Both working and non-working days are included.
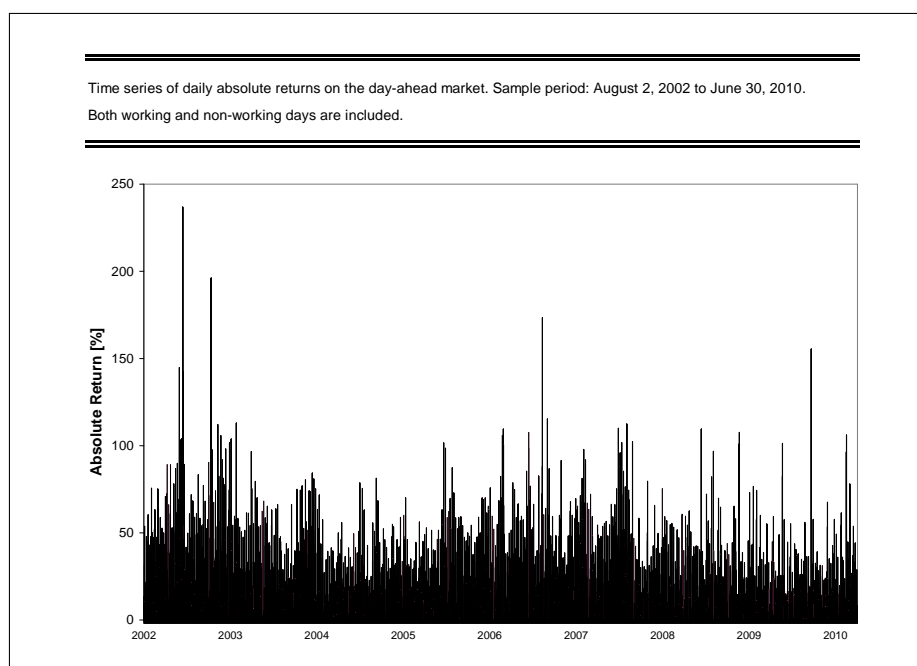
Source: Own work.

negative prices were introduced not until 2008 in the day-ahead market. Second, the current economic crisis was so severe that a decrease in the electricity demand of around 5% was observed in 2009 in the German market.[27] Third, the regulatory framework in Germany was changed. As the EEG[28] aims to increase the ratio of electricity generated based on renewable energies, the absorption of this electricity is compulsory. Thus, the TSOs are forced to inject the electricity generated by these technologies at the time of generation. Starting in 2010, the underlying mechanism was changed and the whole electricity generated within the EEG is now sold in electricity wholesale markets, i.e. the supply at the EEX is increased.[29]

Both observations of the negative daily prices are on non-working days. The first on a Sunday, October 4, 2009, and the second on a Saturday, December 26, 2009. The German Federal Ministry of Economics and Technology assigned an academic study regarding the occurrence of daily negative prices. The results of the study, conducted by Nicolosi et al. (2010), are that negative price spikes are caused by a low load in combination with high supply in terms of electricity generated by renewable energies. Thus, the daily negative price on the day in October 2009 which was a non-working day is probably explained by a low demand in the morning hours[30] and a high electricity supply due to a high wind energy input.

Recalling that seasonality is one of the prevalent characteristics of electricity prices – often observed on three time scales: on a daily, weekly, and monthly scale – I analyze the day-ahead market data in terms of this characteristic. First, I am interested in the weekly seasonality. Therefore, I calculate the average daily price on all weekdays and find that the prices on the weekends are significantly lower. Then I go a step further and use the official trading calendar of the EEX.[31] I calculate the average prices on working and non-working days. Non-working days are weekend days and public holidays. The results show that prices on public holidays during the week are also significantly lower than on normal working days. I hence exclude the public holidays on weekdays from the analysis. As a final result, I get a maximum average daily price – the daily Phelix Base – on Tuesdays (49.56 Euro), almost identical prices on Wednesdays and Thursdays, and slightly lower prices on Mondays (47.05 Euro) and Fridays (45.13 Euro). In contrast, the average prices on Saturdays (35.42 Euro) and on Sundays (27.86 Euro) are significantly lower. The results of this weekly

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[27] Consumption data can be obtained from the European Network of Transmission System Operators for Electricity (www.entsoe.eu) on various time scales.

[28] Cf. section 2.2.3.3 for a discussion of the EEG.

[29] Cf. Nicolosi et al. (2010) for a discussion of the mechanism and the recent change.

[30] On October 4, 2009 only five hours with negative prices are observed. These are the hours 2 to 6. However, in particular the price in hour 3 which is around minus 500 Euro causes an average daily negative price.

[31] The official trading calendar of the EEX is available on the homepage (www.eex.com).

Figure 4.7
Daily Prices on a Weekly Scale Day-Ahead Market

The average daily price is calculated over the period August 1, 2002 to June 30, 2010. Non-working days on weekdays are excluded. The daily price corresponds to the PHELIX Base.
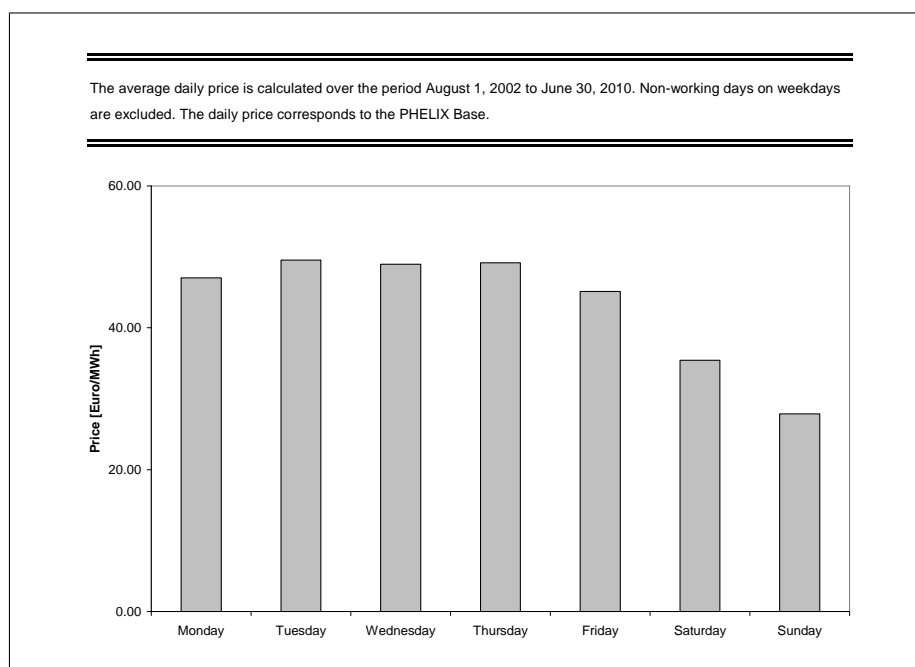
Source: Own work.

analysis are depicted in figure 4.7.

Based on the results above I decide to distinguish in the following between working and non-working days for the day-ahead market and the two other market segments of the spot market. Thus, all price observations from Saturdays, Sundays, and public holidays on weekdays are clustered as *Non-Working Days.* All other price observations are clustered as *Working Days.* The descriptive statistics for the reordered dataset with working and non-working days are reported in tables 4.3 and 4.4.

Analyzing the minimum prices, I count 28 hours with negative prices on working days and 66 hours with negative prices on non-working days.[32] As can be seen in table 4.3 the hours with negative price observations on working days are solely the morning hours, namely in the time period between midnight and 6 am. On non-working days the negative price hours are more mixed and even occur in the afternoon hours. However, the majority of the observations is also observed in the morning hours. The lowest price in the day-ahead market is observed on a non-working day in hour 3 with minus 500.02 Euro on the already above discussed October 4, 2009.

When examining the hourly prices in table 4.3 I detect the expected seasonality on a daily basis. The daily seasonality on working days is depicted in figure 4.8 for a

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[32]Cf. Nicolosi (2010) for a discussion and analysis of these negative hourly prices.

Table 4.3

Descriptive Statistics for Hourly Day-Ahead Market Prices (Working Days)

Descriptive statistics for hourly day-ahead market prices on working days. The covered sample period is August 1, 2002 to June 30, 2010.

Hour 1 stands for the hour contract with delivery between 0 am and 1 am. The following hours are set accordingly.

Hour	Mean	Std.Dev.	Minimum	Median	Maximum	Skewness	Kurtosis	Hour	Mean	Std.Dev.	Minimum	Median	Maximum	Skewness	Kurtosis
1	31.00	12.69	-16.67	28.79	75.01	0.79	0.70	13	60.84	32.56	14.28	53.04	699.81	6.34	94.60
2	27.10	12.89	-151.67	25.51	69.63	-0.83	18.60	14	58.79	31.23	14.63	50.93	699.88	6.44	103.36
3	24.39	12.20	-101.52	23.10	64.09	-0.27	6.72	15	55.71	31.06	13.04	47.96	800.09	8.34	170.28
4	22.17	12.34	-149.94	21.63	60.20	-1.61	24.38	16	52.12	27.62	11.76	45.01	693.23	7.65	150.23
5	23.22	11.69	-101.50	22.38	61.93	-0.70	12.34	17	50.60	24.60	15.23	43.53	300.01	2.82	15.99
6	29.52	11.60	-9.98	27.58	70.51	0.79	0.77	18	55.78	40.94	15.17	45.79	821.90	7.81	104.84
7	38.31	14.79	1.09	35.08	104.93	0.96	1.06	19	60.07	76.87	13.92	47.60	2437	20.88	572.75
8	53.71	24.34	3.03	46.53	301.01	2.35	13.76	20	53.20	27.07	14.54	44.96	300.01	2.55	13.09
9	57.66	28.20	8.02	50.11	437.26	3.33	26.09	21	49.49	20.50	15.81	43.64	194.62	1.30	2.34
10	60.04	30.78	13.39	51.91	499.68	3.67	30.35	22	43.37	16.14	12.48	39.57	118.93	1.08	1.09
11	62.65	37.97	13.61	53.92	998.24	9.41	195.69	23	40.94	14.83	13.93	37.71	94.82	0.95	0.49
12	70.71	65.39	15.54	59.06	2000	17.76	466.73	24	34.21	12.43	9.15	32.13	80.98	0.90	0.64
ALL	46.48	33.98	-151.67	40.09	2437	18.51	965.20								

Source: Own work, based on Pietz (2009*b***).**

Table 4.4

Descriptive Statistics for Hourly Day-Ahead Market Prices (Non-Working Days)

Descriptive statistics for hourly day-ahead market prices on non-working days. The covered sample period is August 1, 2002 to June 30, 2010.

Hour 1 stands for the hour contract with delivery between 0 am and 1 am. The following hours are set accordingly.

Hour	Mean	Std.Dev.	Minimum	Median	Maximum	Skewness	Kurtosis	Hour	Mean	Std.Dev.	Minimum	Median	Maximum	Skewness	Kurtosis
1	30.30	14.28	-119.90	28.30	76.02	-0.60	13.53	13	38.32	15.77	1.88	36.09	99.82	0.97	1.11
2	25.18	14.63	-119.96	23.99	71.07	-1.33	17.42	14	33.65	14.27	-0.04	32.00	91.44	0.86	0.95
3	21.99	22.31	-500.02	21.57	67.93	-14.58	338.59	15	30.14	13.38	-0.74	28.88	87.16	0.78	0.89
4	20.16	13.67	-119.98	19.09	69.52	-1.41	18.33	16	28.16	12.94	-1.93	26.86	82.93	0.75	0.84
5	19.11	13.03	-119.97	17.92	69.92	-0.95	15.67	17	28.76	13.28	0.00	26.90	80.08	0.82	0.89
6	19.15	13.08	-119.98	18.12	69.90	-0.72	14.28	18	34.37	16.07	0.00	31.46	109.95	1.00	1.12
7	15.69	15.34	-199.99	14.52	75.25	-3.31	48.58	19	39.27	17.78	0.26	35.39	119.98	0.93	0.68
8	20.78	15.75	-199.94	19.85	80.68	-2.55	43.12	20	39.86	17.51	1.01	36.05	111.02	0.91	0.77
9	27.08	15.37	-119.96	25.56	91.05	-0.21	9.90	21	37.24	14.88	2.27	34.95	105.31	0.96	1.39
10	33.33	15.89	-36.10	30.91	96.04	0.87	1.62	22	34.82	13.34	2.23	33.40	89.96	0.84	0.99
11	36.91	16.25	0.00	34.38	99.75	1.04	1.43	23	36.56	13.98	4.53	34.81	87.26	0.84	0.64
12	40.36	16.28	1.92	37.66	105.02	1.04	1.27	24	29.94	12.40	-32.80	28.30	75.09	0.57	1.54
ALL	30.05	16.87	-500.02	28.09	119.98	-1.28	51.51								

Source: Own work, based on Pietz (2009*b***).**

Figure 4.8
Hourly Prices on a Daily Scale Day-Ahead Market

The average hourly price is calculated over the period August 1, 2002 to June 30, 2010. Non-working days (also on weekdays) are excluded.

Source: Own work.

better illustration.

On average, the hourly prices on working days are three times higher around midday compared to the early morning hours. A similar pattern is observed for the volatility: When surveying the maximum prices and the third and fourth moment of the distributions I detect hours with frequent price observations in the magnitude of ten times higher than the average price. The dataset even includes four observations of prices above 1,000 Euro: Two in hour 12 (11 am – 12am) on July 25, 2006 and July 27, 2006; two in hour 19 (18 pm – 19 pm) on January 07, 2003 and November 11, 2006. The last observation will be of importance at a later point in this chapter when I discuss the volatility of the estimated risk premia. This one outlier causes a significant bias in the corresponding descriptive statistics for this hour.[33]

The observed maximum prices are the well-known and dreaded price spikes or jumps[34], one of the unique characteristics of electricity prices. The price jumps combined with the high skewness of the price distributions during high demand hours underline the importance of hedging in electricity markets.[35] The two peaks in the average prices,

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[33]Cf. Viehmann (2009) for a discussion of the factors causing these maximum prices in the German market.

[34]Cf. for example Seifert & Uhrig-Homburg (2007) for a discussion of price spikes in electricity markets.

[35]Cf. for example Deng & Oren (2006) for an overview on hedging in electricity markets.

Figure 4.9
Hourly Demand in the German Electricity Market

Hourly load on June 18, 2008 (light bar) and on December 17, 2008 (dark bar) in the German market. The data are obtained from the European Network of Transmission System Operators for Electricity (ENTSOE).
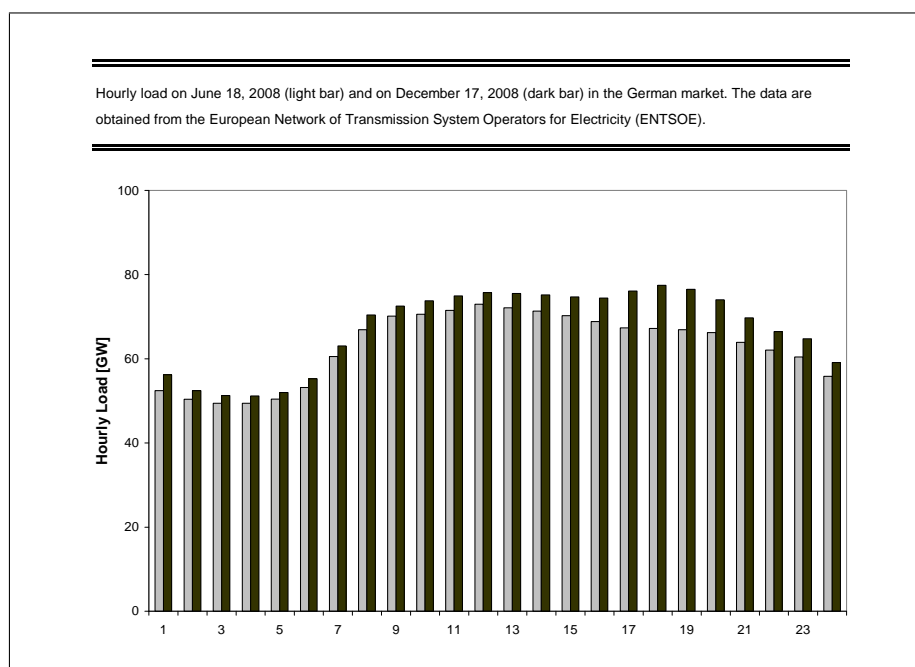
Source: Own work.

the one in hour 12, the other in hour 19 deserve a near discussion. According to Viehmann (2009) I find that peak prices around the hour 12 contract occur in summer months and around the hour 19 contract mainly in winter months.

The price spikes are explained by different demand patterns in summer and winter months. One summer and one winter day are shown, as an example, in figure 4.9. The light bar in the figure depicts the hourly load on June 18, 2008, the dark bar on December 17, 2008. The data are obtained from the European Network of Transmission System Operators for Electricity (ENTSOE). As can be seen the price spikes observed above overlap with peaks in the hourly load.

Coming back to the descriptive statistics in table 4.3, it also stands out that, when comparing working to non-working days, not one individual price spike is observed on a non-working day. The volatility and the skewness of the distributions on non-working days are also significantly lower than on working days. To further analyze this, I order the price data by years, both for the base and peak hours. The descriptive statistics for these data can be found in table 4.5.

The average prices in table 4.5 seem to incorporate a positive drift over the period 2002 to 2008. Except for the year 2007 I observe a steady increase in the average price. A particularly strong increase occurred in 2005 when the EU ETS was in-
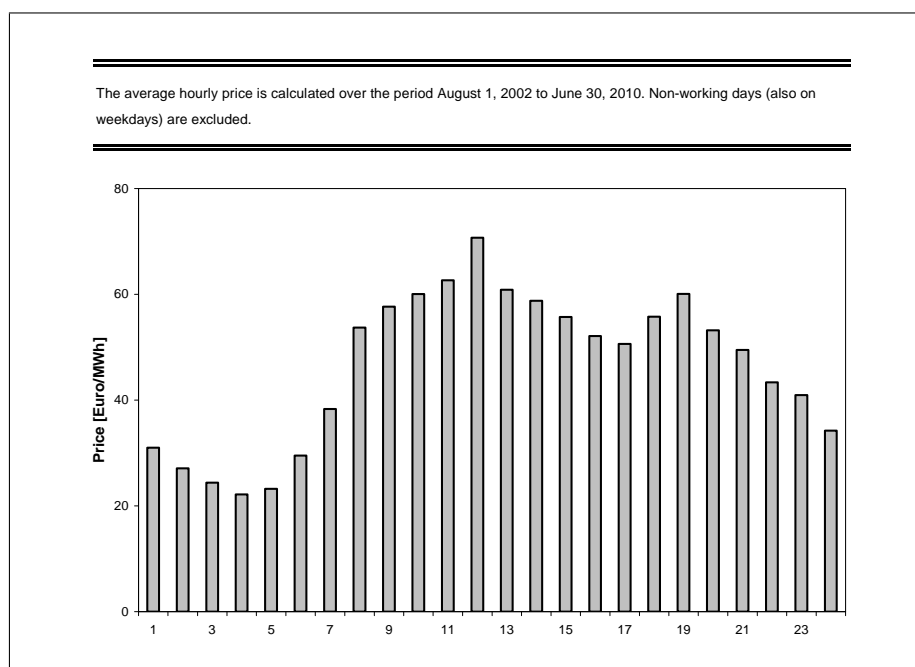
Table 4.5

Descriptive Statistics for Daily Day-Ahead Market Prices by Year

Descriptive statistics for daily day-ahead market prices by year, both for the base and peak hours. Sample period: August 1, 2002 to June 30, 2010. The daily price is calculated as an arithmetic average of the 24 hourly prices.

Year	Base							Peak						
	Mean	Std.Dev.	Minimum	Median	Maximum	Skewness	Kurtosis	Mean	Std.Dev.	Minimum	Median	Maximum	Skewness	Kurtosis
2002	22.98	8.22	3.47	22.89	49.77	0.19	0.09	29.36	11.33	4.14	28.88	75.40	0.47	1.05
2003	29.49	13.07	3.12	29.05	163.46	3.78	32.58	37.00	21.44	0.80	35.24	277.64	5.21	48.71
2004	28.52	6.53	12.06	29.38	46.61	-0.37	0.03	33.99	8.56	11.79	35.12	60.17	-0.13	0.00
2005	45.98	18.42	13.56	42.37	145.97	2.47	9.15	56.00	28.55	16.03	49.62	226.33	2.97	12.12
2006	50.79	24.50	13.98	46.86	301.54	4.42	36.69	63.81	40.98	17.42	57.74	543.72	6.45	63.49
2007	37.99	19.90	5.80	32.71	158.97	2.38	7.98	48.75	30.76	6.76	41.00	248.38	2.77	11.11
2008	65.76	18.12	21.03	65.71	131.40	0.26	0.21	79.43	24.24	21.54	76.86	177.49	0.56	0.47
2009	38.85	11.86	-35.57	37.92	86.36	-0.15	5.84	46.83	14.04	9.47	44.24	114.63	1.10	2.38
2010	41.12	7.13	16.69	41.58	54.07	-0.73	0.86	46.50	9.17	18.19	46.60	65.81	-0.52	0.70

Source: Own work, based on Pietz (2009*b*).

troduced and emission rights were incorporated as a direct production factor in the electricity generation process. The adoption of the emission's right price as a cost factor in electricity generation also represents a potential source for the increasing volatility.[36]

In 2009, a drop of the price level in the magnitude of 40% is to observe. This is probably due to the beginning of the current economic crisis, starting with the collapse of the investment bank Lehmann Brothers in September 2008. Similar to other markets, this was the point-in-time when prices and volume started to decrease in the German electricity wholesale market. However, the significant price decrease is observed in the first quarter 2009. The prices remain at the then reached price level until the end of the sample period.

On average, prices in peak hours are around 20% higher than in base hours. This ratio is quite stable over the whole sample period.[37] The volatility in the peak hours is also significantly higher compared with the base hours.

The last question of interest for the day-ahead market is a potential yearly seasonality. The average month prices are shown in figure 4.10. A maximum price in July, October, and November is observed. May and August seem to be the months with the lowest price.

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[36]Cf. Zachmann & von Hirschhausen (2008) for a discussion of the mechanism behind this observation.

[37]The sample period August 1, 2002 to June 30, 2010 contains 2,891 daily Phelix Base and Phelix Peak prices. Around 75% of the peak prices are between 10% and 30% above the base price; around 90% of the peak prices are between 5% and 35% above the base prices.

Figure 4.10

Monthly Prices on a Yearly Scale Day-Ahead Market

The average monthly price is calculated over the period August 1, 2002 to June 30, 2010. Non-working days on weekdays are excluded. Shown are the montly base prices.
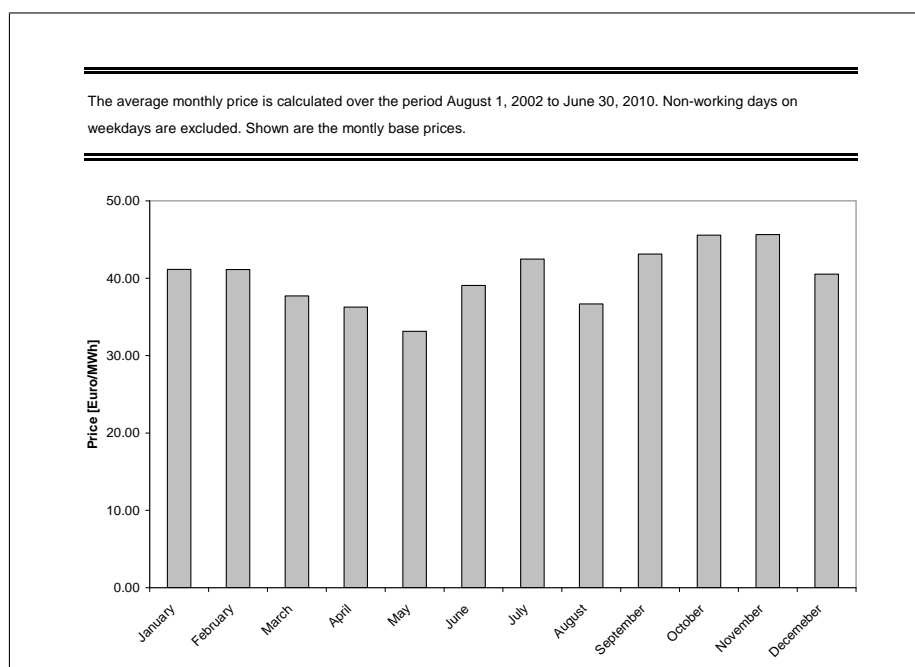
Source: Own work.

However, the results are mixed. When the monthly seasonality is analyzed year by year, it seems that the price peak in summer months is not stable. In 2004, for example, no peak prices in the summer months are observed. On the other side, a clear price peak is observed in July 2007. In 2008, the prices are significantly higher from October to December. A price peak occurs in September and October 2009. Thus, a stable tendency for higher prices around October can be concluded. The prices for summer months, i.e. around July, need to be observed in the coming years to reach a conclusion on the yearly seasonality.

Block Contract Market

Table 4.6 reports the descriptive statistics for the block contract prices. In addition, certain day-ahead market prices are included in the table as well.

The reported data for the day-ahead market in table 4.6 are the corresponding synthetic block contracts.[38] When comparing the block contracts with the synthetic block contracts I observe that the descriptive statistics are very similar except for a higher skewness and kurtosis of the day-ahead market data. This is probably due to

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[38]A synthetic block contract was constructed by bidding for the hour contracts in the day-ahead market which spanned over the time period as covered by the corresponding block contract.

Table 4.6

Descriptive Statistics for Block Contract Market Prices

Descriptive statistics for block contract market prices (first table) and the corresponding (synthetic) block contract prices in the day-ahead market (second table). Sample period: August 1, 2002 to August 31, 2008. The weekend base contract series starts in November 2002.

Block Contracts

	Working Days							Non-Working Days						
	Mean	Std.Dev.	Minimum	Median	Maximum	Skewness	Kurtosis	Mean	Std.Dev.	Minimum	Median	Maximum	Skewness	Kurtosis
Base	47.70	22.56	12.00	40.31	179.33	1.61	4.25	28.26	14.32	5.25	24.23	66.50	0.89	-0.05
Peak	61.04	31.75	16.67	51.07	288.42	2.33	9.11	23.43	11.23	8.00	25.27	42.21	0.01	-0.93
Weekend Base	-	-	-	-	-	-	-	30.56	13.23	10.68	24.75	66.88	0.69	-0.76

Day-Ahead Market Contracts

	Working Days							Non-Working Days						
	Mean	Std.Dev.	Minimum	Median	Maximum	Skewness	Kurtosis	Mean	Std.Dev.	Minimum	Median	Maximum	Skewness	Kurtosis
Base	45.29	21.22	12.40	38.98	301.54	2.83	19.63	28.43	12.56	3.12	25.54	80.42	0.94	0.71
Peak	57.28	32.00	15.86	48.41	543.72	4.71	47.92	32.29	14.25	0.80	28.97	86.69	0.96	0.72
Weekend Base	-	-	-	-	-	-	-	29.56	11.63	9.24	26.04	70.95	0.87	0.14

Source: Own work, based on Pietz (2009*b*).

the frequent price spikes in this market.

I note that the high number and the uneven distribution of the non-trading days in the block contract market have to be taken into account when the results obtained in the following are interpreted. Another systematic pattern in the data, also already observed by Ronn & Wimschulte (2009), is a higher number of days without trading in contracts with delivery on Mondays.

Intraday Market

Before providing descriptive statistics for the intraday market, I have to decide which price time series is appropriate for the estimation of the risk premia – either the last price or the average price. The last price is the price of the last trade in an hour contract; the average price the average price of all trades in an hour contract. There is no information on the number and timing of individual trades in a certain hour contract in the intraday market available. Thus, the only secure information on these two prices is that the last price is, in the case that more than one trade in an hour contract took place, chronological later than the average price. Comparing the two time series with regard to systematic differences no obvious results are found. The mean of the average price time series is slightly higher than the one of the last price

Table 4.7

Descriptive Statistics for Hourly Intraday Market Prices (Working Days)

Descriptive statistics for hourly intraday market prices on working days. The price of the last trade in the intraday market is used. Sample period: September 25, 2006 to June 30, 2010. Overall 20,837 price observations on working days are included.

Hour	Mean	Std.Dev.	Minimum	Median	Maximum	Skewness	Kurtosis	Hour	Mean	Std.Dev.	Minimum	Median	Maximum	Skewness	Kurtosis
1	35.17	18.87	-200.00	34.00	84.00	-4.61	57.19	13	65.62	27.44	16.00	60.00	220.00	1.33	2.97
2	31.01	17.28	-200.00	30.00	75.00	-3.09	41.75	14	62.85	26.60	15.00	58.00	210.00	1.35	3.01
3	27.89	17.83	-200.00	28.00	79.00	-3.18	37.95	15	59.78	26.41	5.00	55.00	250.00	1.41	4.16
4	24.87	19.12	-200.00	25.00	70.00	-4.49	49.93	16	57.15	24.63	10.00	52.00	210.00	1.32	3.15
5	26.82	16.86	-200.00	27.00	76.00	-3.06	41.46	17	57.16	26.82	7.00	51.00	300.00	1.90	9.16
6	32.73	18.06	-200.00	32.00	84.00	-2.93	36.56	18	64.31	42.03	15.00	58.00	500.00	4.84	37.69
7	47.73	18.98	-10.00	45.50	111.00	0.41	-0.12	19	67.57	42.07	5.00	60.00	500.00	4.07	30.03
8	63.76	27.11	12.00	60.00	330.00	1.81	11.80	20	61.91	28.76	15.00	57.00	270.00	1.57	5.32
9	70.21	33.15	16.00	63.00	400.00	2.46	15.90	21	54.78	22.59	1.00	51.00	190.00	1.08	2.26
10	68.96	30.48	21.00	60.50	250.00	1.56	4.09	22	49.06	18.12	15.00	46.00	129.00	0.77	0.56
11	69.20	31.41	21.00	62.38	300.00	1.79	6.09	23	47.76	17.86	1.00	45.00	199.00	1.12	5.03
12	72.77	35.18	22.50	65.00	300.00	1.97	6.08	24	39.91	15.38	5.00	38.00	149.00	0.80	2.40
ALL	53.42	30.50	-200.00	48.00	500.00	2.10	18.95								

Source: Own work, based on Pietz (2009b).

time series; the volatility of the average price is slightly lower than the one of the last price.

I believe that the last price is the one to be used for the following analysis. This is due to the theoretical framework behind the use of the risk premia approach. I interpret market segments of the spot market with earlier trading as futures markets. A day-ahead market contract is, in general, interpreted as a future with a time-to-delivery of one day. The time difference between trading in these two market segments is hence the main characteristic of interest. The last price is the price observation which maximizes the temporal difference between trading in the day-ahead and in the intraday market. Thus, it is the price which should be used. However, considering the thin trading in the intraday market and the presumably uneven distribution of trades during the permitted trading phase for a specific contract, I conduct the analysis also based on the average prices. I report potential differences in the results in the following.

Descriptive statistics for hourly last prices on working and non-working days on the intraday market are reported in table 4.7 and table 4.8, respectively. The intraday market price data are similar to the day-ahead market price data.[39] Perhaps the

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[39] The descriptive statistics for the intraday market cannot (directly) be compared with the descriptive statistics for the day-ahead market as the sample period in the later case is much longer and a strong increase in the prices was observed over the years.

Table 4.8

Descriptive Statistics for Hourly Intraday Market Prices (Non-Working Days)

Descriptive statistics for hourly intraday market prices on non-working days. The price of the last trade in the intraday market is used.

Sample period: September 25, 2006 to June 30, 2010. Overall 9,041 price observations on working days are included.

Hour	Mean	Std.Dev.	Minimum	Median	Maximum	Skewness	Kurtosis	Hour	Mean	Std.Dev.	Minimum	Median	Maximum	Skewness	Kurtosis
1	28.47	86.04	-1499	33.00	79.50	-17.00	301.72	13	42.89	16.85	1.00	39.35	101.00	0.76	0.41
2	25.45	56.67	-950.00	29.75	93.00	-15.49	264.51	14	37.81	16.61	-75.00	36.00	85.50	-0.37	5.04
3	23.40	49.86	-800.00	26.00	69.00	-14.12	228.56	15	32.60	22.26	-250.00	32.00	87.50	-5.73	67.71
4	22.76	25.70	-295.00	25.00	68.00	-7.24	81.88	16	30.25	42.45	-750.00	31.00	95.00	-15.23	277.70
5	22.39	19.51	-190.00	23.50	69.00	-3.92	41.07	17	32.69	20.57	-200.00	31.00	90.00	-3.54	40.49
6	22.44	18.59	-170.00	21.50	66.00	-3.10	32.07	18	41.46	19.11	-2.00	39.00	105.00	0.49	-0.08
7	20.91	23.67	-198.00	21.00	80.00	-3.83	30.99	19	47.64	21.78	6.00	45.00	142.00	0.83	1.20
8	26.22	22.94	-199.00	26.00	77.00	-3.92	35.63	20	47.64	21.27	-2.00	45.00	125.00	0.79	0.70
9	31.93	20.96	-190.00	32.00	95.00	-3.18	34.53	21	43.55	17.82	-1.00	41.00	113.00	0.64	0.39
10	40.05	17.97	1.00	38.00	105.00	0.62	0.54	22	40.30	17.46	-90.00	39.00	89.00	-0.88	7.55
11	42.74	17.02	6.00	40.00	102.00	0.76	0.68	23	42.33	16.96	1.00	40.00	96.00	0.44	-0.24
12	44.87	17.03	1.00	41.00	103.00	0.75	0.69	24	31.23	48.29	-800.00	33.00	89.00	-13.87	231.66
ALL	34.77	32.42	-1499	34.50	142.00	-20.83	787.73								

Source: Own work, based on Pietz (2009*b*).

most striking differences are the significantly lower maximum prices in the intraday market and the consequential smaller skewness and kurtosis of the price distributions for the intraday market.

Moreover, similar to the day-ahead market, negative prices are observed in the intraday market, both on working and non-working days. On working days I count 71 hours with a negative price over the sample period, on non-working days 113 hours. The lowest price is observed on a non-working day with minus 1,499 Euro in hour 1. Similar to the day-ahead market, the majority of the negative price observations occurs in the morning hours.

Figure 4.11 depicts the price time series of four selected hour contracts over the whole sample period on working days. Appendix A contains the time series of all 24 hour contracts on working days to illustrate the different characteristics in dependence of the delivery hour. In addition, Appendix B contains the time series of all 24 hour contracts of the day-ahead market on working days in the period January 2, 2008 to June 30, 2010 to amplify the differences between these two market segments.

The time series of the hour 1, 7, 13, and 19 contracts on working days are shown in figure 4.11. It is to consider that the y-axis is solely identical for the hour 13 and hour 19 contract. The time series of the hourly contracts show both different price levels and volatilities. The time series of the hour 1 contract is, for example, quite

Figure 4.11
Selected Hourly Price Time Series Day-Ahead Market

Time series of hourly price over the period January 2, 2008 to June 30, 2010. The price time series contain price observations only for working days. Missing values are due to non trading in the paricular contract.
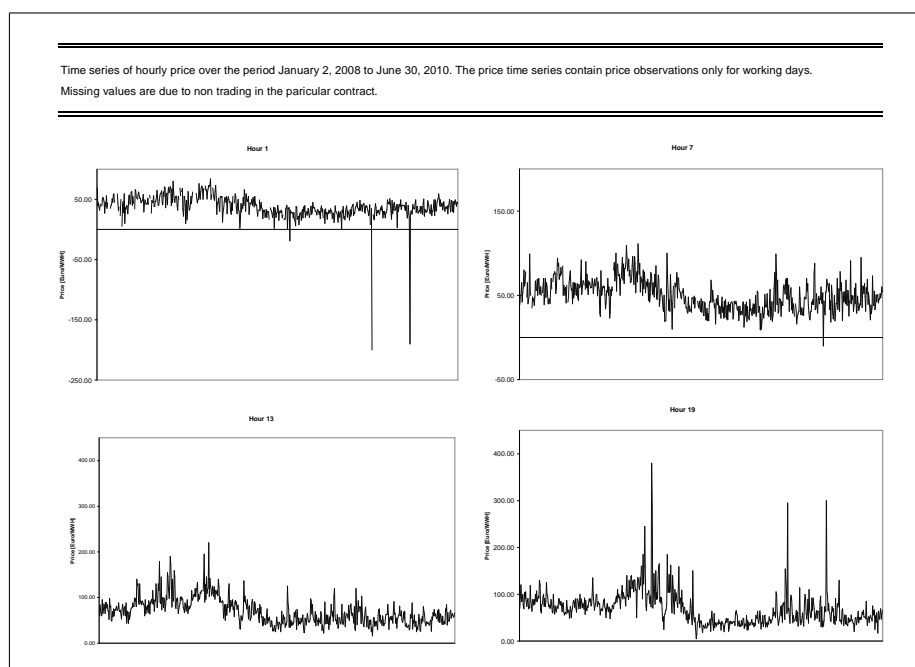
Source: Own work.

smooth at the beginning of trading in the intraday market and then exhibits two negative prices in 2009. The hour 19 contract on the other side is characterized by a high volatility and the regular occurrence of price spikes. Finally, the hour 7 and hour 13 contracts reveal a relatively smooth timely evolution.

The EEX provides no daily prices from the intraday market; this is in opposite to the day-ahead market for which the daily Phelix Base and Peak is published. To allow a comparison of these two market segments, I calculate a daily price for the intraday market similar to the daily Phelix Base. I calculate the daily price as an average of all hourly prices within a day. However, due to the low liquidity in the intraday market in particular at the beginning of trading, I have to deal with days with less than 24 hourly prices. To overcome this data problem I decide to fill gaps in the dataset, i.e. hours without an observed price, with the next observed price in the same hour contract. Thereby, I distinguish between working and non-working days. Thus, for example, a gap in the dataset for the hour 7 contract with delivery on a Saturday is filled with the next observed price in this hour contract on a non-working day. The resulting daily price is shown in figure 4.12.

Compared with the daily prices in the day-ahead market – as shown in figure 4.5 – it first stands out that no price spikes occur in the intraday market, at least not on a

Figure 4.12
Daily Prices Intraday Market
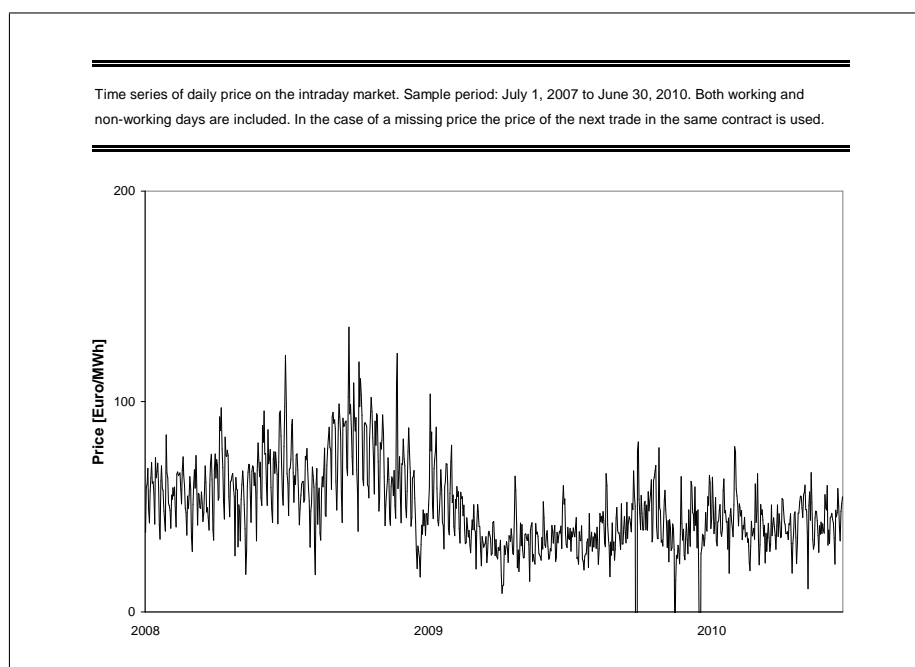
Source: Own work.

daily scale. Second, similar to the two negative price observations in the day-ahead market, negative daily prices are observed in the intraday market. In the second half of 2009 five daily negative prices are observed. Third, beginning with the financial and economic crisis in 2008, after a period of high volatility, a decrease in both price level and volatility is observed.

4.4.2.2 Futures Market

The analysis of the futures market excludes the month future with the shortest time-to-delivery due to its trading in the delivery month. The settlement of a cash-settled future consists in the payment of the difference between the price at opening the position and the realized average spot price during the delivery period.[40] Thus, trading in the delivery period effectively leads to a conversion to a future with a shorter delivery period. This results in a lower volatility and a convergence of the futures price to the average spot price. This effect is shown in figure 4.13.

Three time series are displayed in figure 4.13. The first, shown as a continuous dashed line, is the daily day-ahead market price. The second, which is recognizable through the weekend interruptions and a smooth evolution, is the daily price of the

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[40]The daily mark-to-market mechanism is ignored in this analysis.

Figure 4.13
Month Base Future and Underlying Spot Price

The continuous dashed line is the daily day-ahead market price. The time series with the weekend interruptions is the daily price of the month base future. The solid line is the average day-ahead month price during the delivery month.
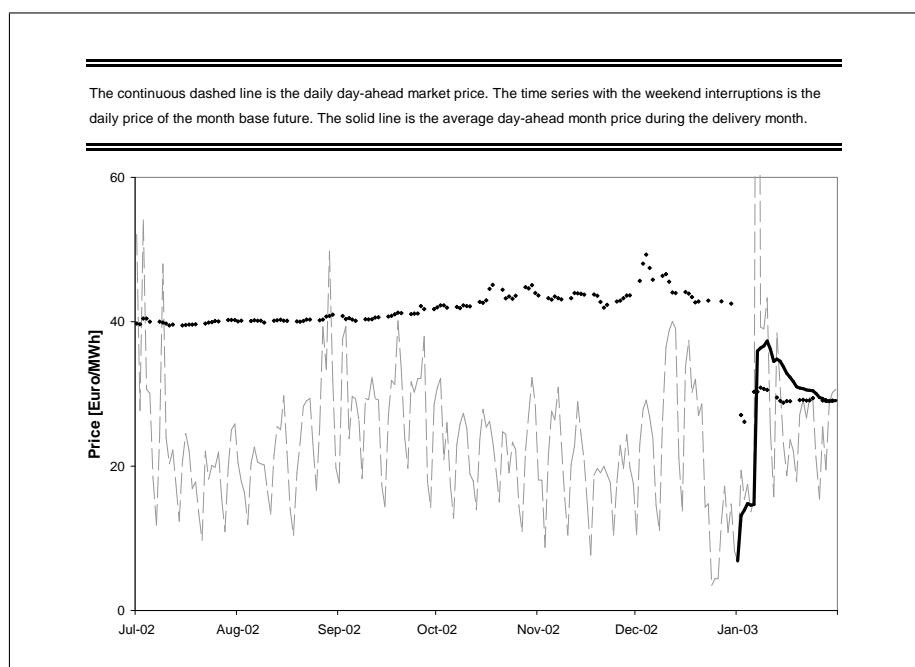
Source: Own work.

month base future with delivery in July 2003. Finally, the average monthly price during the delivery month is displayed as a solid line, i.e. the number of data points used for this calculation increases with the time. The y-axis is set between 0 and 60 Euro to illustrate the time series. Thereby, one data point, a daily price of 163.46 Euro on July 1, 2003, is not shown. It can be seen that the futures price converges to the average monthly price at the end of the trading period of the future.

The terminology which is employed for the month futures can be clarified through the example of the futures price series in figure 4.13. The shown future is the month base future with delivery in January 2003. This future was traded between July 1, 2002 and January 31, 2003. I handle the price data of this future as follows: During trading in July 2002 this future is termed as *six month future*, in August as *five month future*, and so on. Finally, in December 2002, I term this future as *one month future*. January 2003 data are excluded due to the problems discussed above regarding futures being traded in their delivery period.

The final dataset comprises 90 month futures observed over their whole trading period. They are characterized by their delivery month, e.g. January 2003. Considering the definition of the ex post risk premium and the problem of separating forecast errors and risk premia the low number of contracts is identified as a potential problem

Table 4.9
Descriptive Statistics Month Base Futures

The first table contains descriptive statistics on the price data, the second on the return data (computed as log returns). The data are monthly (daily data in brackets). Price data in Euro, return data in %.

Future	Mean	Std.Dev.	Minimum	Median	Maximum	Skewness	Kurtosis
One	43.6	15.4	21.31	38.93	89.46	0.87	0.19
	(43.59)	(15.57)	(20.8)	(39.2)	(98.41)	(0.9)	(0.27)
Two	44.48	15.76	22.33	41.29	92.79	0.81	0.11
	(44.46)	(15.87)	(21.48)	(41.01)	(96.76)	(0.85)	(0.17)
Three	44.95	16.15	21.68	41.09	91.75	0.93	0.51
	(45.03)	(16.26)	(21.22)	(41.21)	(98.23)	(0.95)	(0.56)
Four	45.14	16.17	21.18	42.22	95.44	1	0.98
	(45.24)	(16.28)	(20.8)	(42.11)	(101.94)	(1.03)	(1.01)
Five	45.45	16.21	21.3	44.02	96	0.95	1.07
	(45.54)	(16.31)	(20.93)	(44)	(101)	(0.97)	(1.07)
Six	45.54	15.9	20.5	43.44	95.32	0.86	0.93
	(45.61)	(15.98)	(20.35)	(43.53)	(102.75)	(0.89)	(0.96)
One	0.84	13.52	-33.7	2.77	43.26	-0.11	0.44
	(0.04)	(3.15)	(-15.47)	(-0.08)	(27.58)	(1.73)	(15.21)
Two	0.71	13.13	-38.48	1.42	32.82	-0.14	0.16
	(0.03)	(2.66)	(-18.05)	(0)	(24.83)	(0.89)	(17.22)
Three	0.79	13.17	-35.68	1.36	43.93	0	0.73
	(0.04)	(2.55)	(-23.91)	(0)	(32.18)	(1.86)	(34.72)
Four	0.72	11.14	-34.73	1.75	31.46	-0.31	0.86
	(0.03)	(2.43)	(-19.97)	(0)	(33.67)	(1.29)	(39.34)
Five	0.83	11.36	-28.22	1	27.86	-0.11	-0.06
	(0.04)	(2.39)	(-22.25)	(0)	(30.75)	(1.5)	(36.66)
Six	0.71	10.86	-34.49	1.48	24.16	-0.48	0.48
	(0.03)	(2.38)	(-25.7)	(0)	(27.84)	(0.07)	(36.51)

Source: Own work, based on Pietz (2009*a***).**

for the interpretation of the later results and their robustness.

Using the terminology introduced above, I report in table 4.9 and table 4.10 the descriptive statistics on the month futures, both for the base and the peak future.

The upper part of the table contains the descriptive statistics on the price data with monthly frequency. The lower part of the table contains the descriptive statistics on the return data. The returns are calculated as log returns. The corresponding values for data with daily frequency are reported in brackets. The monthly data are calculated as the arithmetic average of all prices within one month.

Comparing the daily and monthly prices a smoothing is observed. This was expected due to the lower sensitivity of monthly prices to price spikes. The average price increases between the first and the third month future. Thereafter, it remains constant. The prices for peak futures are on average 18 to 19 Euro or around 41% higher than the base future prices. I observe a decreasing volatility with increasing time-to-delivery. Without further examination, I conclude that this may be interpreted as the Samuelson Effect.[41]

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[41]The Samuelson Effect (Samuelson (1965)) indicates that the volatility of futures prices decreases as time-to-delivery increases. This is explained by a lower sensitivity of long-term futures to information inflow due to a longer remaining adjusting period.

Table 4.10
Descriptive Statistics Month Peak Futures

The first table contains descriptive statistics on the price data, the second on the return data (computed as
log returns). The data are monthly (daily data in brackets). Price data in Euro, return data in %.

Future	Mean	Std.Dev.	Minimum	Median	Maximum	Skewness	Kurtosis
One	61.15	21.89	32.49	54.34	130.77	0.95	0.25
	(61.17)	(22.33)	(31.55)	(54.34)	(141.56)	(1.01)	(0.39)
Two	62.89	22.49	33.34	56.89	131.4	0.87	0
	(62.87)	(22.73)	(32.14)	(56.63)	(136.91)	(0.91)	(0.11)
Three	63.55	22.78	31.9	58.79	130.11	1	0.53
	(63.67)	(22.99)	(31.5)	(58.25)	(139)	(1.03)	(0.57)
Four	63.86	22.51	31.24	60.7	131.08	1.09	1.07
	(64.01)	(22.68)	(30.68)	(60.29)	(143)	(1.11)	(1.07)
Five	64.41	22.27	31.21	61.34	131.3	1	0.99
	(64.54)	(22.42)	(30.88)	(61.13)	(143)	(1.01)	(0.96)
Six	64.61	21.91	30.61	61.68	134.19	0.95	0.96
	(64.69)	(22.05)	(30.25)	(60.32)	(144.1)	(0.96)	(0.95)
One	0.64	17.15	-44.87	2.14	51.38	-0.06	0.61
	(0.03)	(3.99)	(-22.63)	(-0.12)	(43.72)	(1.86)	(20.04)
Two	0.55	15.68	-47.23	0.97	49.45	0.08	0.95
	(0.03)	(3.11)	(-21.31)	(-0.02)	(39.59)	(1.94)	(26.22)
Three	0.62	14.57	-39.01	1.03	35.53	-0.23	0.1
	(0.03)	(2.82)	(-31.55)	(0.01)	(35.82)	(0.94)	(36.7)
Four	0.58	12.03	-38.11	1.41	27.22	-0.58	0.48
	(0.03)	(2.71)	(-29.88)	(0)	(25.31)	(0.46)	(36.38)
Five	0.73	12.14	-31.37	0.9	25.6	-0.14	-0.18
	(0.04)	(2.55)	(-28.95)	(0)	(26.29)	(0.61)	(32.4)
Six	0.61	11.46	-37.85	1.66	23.39	-0.56	0.71
	(0.03)	(2.32)	(-25.28)	(0)	(19.45)	(-0.83)	(31.62)

Source: Own work, based on Pietz (2009a).

The observed high maximum values in futures prices are unexpected, in particular
when compared to the realized monthly prices on the day-ahead market serving
as underlying of the futures market as shown in figure 4.14. It is apparent that
the maximum future prices are higher than the highest realized prices on the spot
market. In addition, the positive skewness suggests that several observations were
taken in this price region. There also seems to be a tendency for a co-movement of
spot and futures prices which results in a high correlation between the time series.
For a further analysis of this behavior I run a regression of the futures prices on
the spot prices. When doing so, I take into consideration that a regression of two
time series is only meaningful when both time series are stationary or cointegrated.
Otherwise misleading results could be obtained due to spurious regression. When
testing for unit roots in the time series using the Dickey-Fuller-Test, I find that the
null hypothesis (existence of a unit root) cannot be rejected. Tests for cointegration
deliver mixed results. I hence drive a regression with first differences and find a
relationship between the spot and the futures prices.[42]

The above results are also found in a recent work by Redl et al. (2009) who analyze
the price formation in the futures markets of the EEX and of the Nord Pool. The

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[42]However, the results are mixed and neither easy to interpret. Due to space considerations and
the work of Redl et al. (2009) discussed below I do not report the results here.

Figure 4.14
Monthly Price Day-Ahead Market

Monthly prices on the day-ahead market. The monthly prices are calculated as the arithmetic average of the hourly prices within the month. The straight line represents the monthly Phelix Base, the dashed line the monthly Phelix Peak.
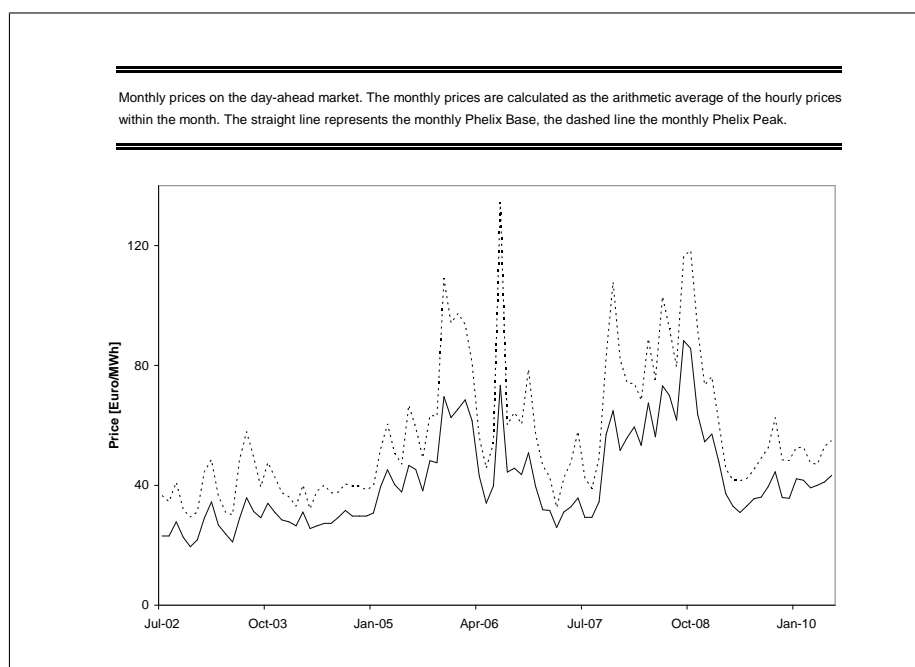
Source: Own work.

authors find that fundamental expectations or risk considerations cannot fully explain the difference between futures and spot prices. They conclude that an adaptive price formation effect is apparently existent in both markets. This is interpreted as evidence for the existence of systematic forecast errors. These findings question the assumption of rational expectations underlying every analysis of risk premia from an ex post perspective. However, the results have to be seen as primarily and it is possible that, for example, market power is responsible for this effect. Further research on this topic is definitely necessary.

4.4.3 Risk Premia in the German Electricity Market

4.4.3.1 Risk Premia in Spot Contracts

The results of the empirical analysis of the spot market are reported separately for the block contract market and the day-ahead market. Furthermore, a potential term structure of risk premia and potential drivers of the risk premia are discussed.

Risk Premia in the Block Contract Market

The risk premia in block contracts are estimated as the price difference between the

Table 4.11
Risk Premia in Block Contracts

Risk premia in block contracts on working days. The absolute and relative risk premia are reported. ***, ** and * indicate significance at the 1%, 5% and 10% level; the Newey-West estimator is used to obtain robust standard errors.

	Absolute Risk Premia			Relative Risk Premia		
	Mean	Median	Std.Dev.	Mean	Median	Std.Dev.
Base	0.79**	0.64	11.34	1.07**	1.35	17.12
Monday	2.11***	1.41	6.19	4.25***	3.29	10.97
Tuesday	0.03	0.81	16.69	-0.9	1.47	28.45
Wednesday	1.12*	0.69	9.57	1.34*	1.53	12.65
Thursday	-0.17	0.27	11.52	-0.03	0.56	13.96
Friday	1.21*	0.40	8.96	1.47	1.04	11.84
Peak	1.55**	1.51	20.37	1.9***	2.90	22.93
Monday	3.41***	2.00	11.60	4.87***	4.20	12.87
Tuesday	-0.16	2.24	30.14	-1.04	4.57	40.27
Wednesday	1.53	0.99	15.53	1.67*	2.14	15.05
Thursday	0.44	0.29	21.66	1.05	0.76	17.44
Friday	3.15***	1.62	15.29	3.84***	3.22	13.48

Source: Own work, based on Pietz (2009a).

block contracts and the corresponding day-ahead market contracts, i.e. the block contract market is regarded in this section as a futures market in relation to the day-ahead market.

The estimated risk premia in block contracts are summarized in table 4.11. Results are reported for working days only as all results for non-working days are statistically insignificant. The table contains results for the base load and the peak load contracts. I apply the Newey-West estimator to receive autocorrelation and heteroscedasticity robust results.

Table 4.11 reveals the existence of risk premia, in both base load and peak load contracts, with statistically significant results. A high risk premium, significant at the 1% level, is observed in base load and peak load contracts, in particular on Mondays. In addition, significant risk premia in the base load contracts are observed on Wednesdays and Fridays as they are also in the peak load contracts on Fridays. Overall, the risk premia in both contracts are significant at the 5% level and have a magnitude of 0.79 Euro in the base load contracts and of 1.55 Euro in the peak load contracts. Compared with the average prices of the base load and peak load contract the results imply that on average 1.66% and 2.54%, respectively, of the block contract price is paid for the hedging of price risk. For the block contract with delivery on Mondays the ratio even goes up to around 5%.

The obtained results seem to confirm the theory discussed above. Market participants are apparently willing to pay a risk premium to secure future prices. The earlier the hedging is possible, the more market participants are willing to pay. From this perspective, especially the risk premium in block contracts with delivery on Mondays should be relatively high since these contracts have a time-to-delivery of three days, hence forcing market participants to forecast the spot price three days in advance. The high observed risk premia in this contract match the theoretical prediction. Furthermore, the observation that the block contracts with delivery on Mondays were considerably less often traded than the other contracts can also be regarded as support for the high risk of these contracts.

The obtained results for the block contract market confirm the results of Ronn & Wimschulte (2009). Although pursuing a different goal, the authors analyze the sample period August 1, 2002 to September 30, 2007 and estimate the risk premia in the block contracts. Using an extended sample period the results are consistent with the results reported in table 2 of their paper.

Risk Premia in the Day-Ahead Market

Risk premia in day-ahead market contracts are estimated as the price difference between the day-ahead market and the intraday market contracts with the same delivery hour. In this analysis the day-ahead market is regarded as a futures market in relation to the intraday market. I use the last price of the intraday market contracts and separately estimate the risk premia in contracts with delivery on working and non-working days.

Tables 4.12 and 4.13 contain the results for the risk premia estimation in day-ahead market contracts. I report the average risk premium, the median value as a robustness check and the standard deviation.[43] Both the absolute and relative risk premia are reported. The Newey-West estimator is used to get autocorrelation and heteroskedasticity consistent results.

The average risk premium on working days amounts to minus 0.10 Euro. For non-working days the analysis yields an average risk premium of 1.89 Euro. The average risk premia on non-working days are statistically significant at the 1% level; for the risk premia on working days no statistical significance is found. For working days the median is slightly higher, for non-working days slightly lower. However, the mean and median are still in the same range. It stands out that the daily average risk premia seem to be higher on non-working days than on working days.

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[43]The median value is perhaps a better measure to analyze the ex post risk premia (estimated with a small dataset) since the average value is sensitive to price spikes in one of the markets.

Table 4.12

Risk Premia in Day-Ahead Market Contracts (Working Days)

Risk premia in hour contracts traded in the day-ahead market on working days. Both the absolute and relative risk premia are reported. ***, ** and * indicate significance at the 1%, 5% and 10% level; the Newey-West estimator is used to obtain robust standard errors.

	Absolute			Relative				Absolute			Relative		
Hour	Mean	Median	Std.Dev.	Mean	Median	Std.Dev.	Hour	Mean	Median	Std.Dev.	Mean	Median	Std.Dev.
1	1.37**	1.03	14.73	-1.28	3.13	109.55	13	1.01	1.84	15.57	0.65	2.56	23.24
2	0.92	0.84	13.52	-8.79	2.39	180.72	14	0.84	2.08	13.87	0.73	3.32	21.97
3	0.73	1.60	12.53	-6.71	4.58	206.94	15	0.46	1.21	13.51	0.6	2.31	22.51
4	0.82	0.58	14.31	-240.55	2.22	4093.19	16	-0.65	0.10	13.14	-1.92*	0.18	22.70
5	0.43	0.31	14.22	-141.24	1.44	2845.25	17	-1.07*	0.05	14.00	-1.61	0.14	23.08
6	2.21***	2.66	14.22	7.22*	6.82	85.51	18	-1.61**	-0.65	15.91	-2.68***	-1.07	21.91
7	-0.85	-0.07	13.15	-3.27**	-0.15	31.83	19	-2.38***	-0.41	21.33	-3.23***	-0.65	28.01
8	0.17	1.59	16.86	-2.22	2.55	31.27	20	-0.53	0.50	15.70	-1.02	0.69	22.61
9	-5.33***	-2.54	19.51	-8.5***	-3.89	31.31	21	2.21***	2.03	13.09	2.41**	3.74	22.95
10	-1.99***	-0.39	14.05	-3.15***	-0.62	21.16	22	0.51	0.95	10.76	0.17	1.82	22.18
11	0.08	1.01	17.10	-0.68	1.67	22.97	23	-0.74*	-0.73	9.68	-1.86**	-1.26	21.03
12	1.15	1.90	21.31	0.43	2.14	24.84	24	-0.04	0.07	9.41	-0.71	0.11	25.74
Overall	-0.1	0.56	15.02	-17.01**	1.14	1008.60							

Source: Own work, based on Pietz (2009b).

A possible explanation for the higher risk premia on non-working days is the observation that electricity buyers primarily participate in the day-ahead market. In particular, they seem to avoid the intraday market – due to lack of liquidity – on non-working days.[44] This behavior should result in a positive price difference, i.e. risk premia, between these two market segments. Furthermore, the intraday market, as the electricity buyer cover their demand in the day-ahead market, becomes a buyers market. The frequent occurrence of negative price spikes, as is seen in tables 4.7 and 4.8, backs this argumentation.[45]

The hourly risk premia are volatile and they frequently change in sign. This corresponds to results from other markets, as for example to the results reported by Longstaff & Wang (2004) for the PJM market. I find significant risk premia in 8 of the 24 day-ahead market contracts with delivery on working days. The risk premia are positive in the early morning hours and in the afternoon. The statistically significant risk premia are mainly negative and found in the morning and evening hours. On non-working days 10 statistically significant risk premia are detected. Comparing the median values and standard deviation of the separate hour contracts only the

[44]Cf. Weber (2010) for a discussion of potential reasons for the low liquidity in the German intraday market.

[45]Also in discussion with practitioners active in electricity trading this point of view regarding the intraday market became clear.

Table 4.13

Risk Premia in Day-Ahead Market Contracts (Non-Working Days)

Risk premia in hour contracts traded in the day-ahead market on non-working days. Both the absolute and relative risk premia are reported. ***, **
and * indicate significance at the 1%, 5% and 10% level; the Newey-West estimator is used to obtain robust standard errors.

Hour	Absolute			Relative			Hour	Absolute			Relative		
	Mean	Median	Std.Dev.	Mean	Median	Std.Dev.		Mean	Median	Std.Dev.	Mean	Median	Std.Dev.
1	9.06	2.68	92.04	11288.09	7.19	183139	13	2.75***	3.09	11.50	3.58**	6.30	26.48
2	5.1	1.03	52.90	-63.9	2.84	1248.37	14	2.45***	1.87	11.59	15.32	4.19	162.34
3	2.4*	1.40	22.59	447.41	4.99	7734.91	15	3.73***	2.42	19.91	-13.2	6.28	442.71
4	0.95	-0.06	17.03	-168.61	-0.34	2778.67	16	4.44	1.63	47.41	-3.13	4.04	604.68
5	0.12	-0.09	12.93	-529.24	-0.04	9080.70	17	1.21	1.43	18.10	64.78	3.96	1653.55
6	-0.08	-0.57	13.45	23.19	-0.74	2355.31	18	-0.79	-0.34	13.18	-4.49*	-0.60	38.46
7	-2.88**	-3.12	18.18	459.88	-7.62	7636.55	19	-0.59	0.93	14.83	-1.93	1.88	32.02
8	-1.4	-1.64	16.13	-100.47	-3.23	7861.78	20	0.64	0.69	14.35	1.21	1.51	29.02
9	1.12	0.42	12.23	705.54	1.19	12025.4	21	1.71*	0.97	13.11	2.75	2.46	28.68
10	0.24	0.09	11.11	-0.96	0.40	39.34	22	2.53***	2.37	14.03	6.17**	4.51	47.05
11	1.73***	1.24	9.84	2.11	2.67	22.80	23	1.33	1.13	12.55	1.85	2.59	29.28
12	3.26***	2.97	10.01	4.41***	5.09	22.65	24	6.42**	2.12	50.61	-6.7	5.48	221.81
Overall	1.89***	1.01	28.99	490.78	2.88	37066.1							

Source: Own work, based on Pietz (2009*b*).

hour 19 contract on working days stands out. The explanation for the high volatility is one extreme price observation in the day-ahead market.[46] The highest positive risk premia on working days is found in the hour 6 and hour 21 contracts, the lowest in the hour 9 contract. Using the average prices of the intraday market to estimate the risk premia in the individual hour contracts, I find no systematic differences in the results.

Regarding the results for the relative risk premia, the high volatility of the prices in the two spot market segments is clearly visible in the results. In particular the results for non-working days, and here in the early morning hours, are strongly influenced by outliers.[47]

To illustrate the high volatility of the risk premia the time series of the risk premia in four selected hour contracts are plotted in figure 4.15.

The selected hour contracts shown in figure 4.15 are equally spread over the day, with a constant five hour gap in-between. Thus, the risk premia in hour contracts with fundamental different demand profiles are shown. The vertical axes of the four

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[46]The extreme observation in hour 19 occurs on November 07, 2006 with a price of 2,436.63 Euro. The exclusion of this price observation from the dataset results in a volatility for the hour 19 contract which is comparable to the volatility of the other hour contracts.

[47]I do not adjust the dataset for outliers as the analysis of the absolute risk premia is for the spot market in the foreground.

Figure 4.15
Selected Risk Premia Time Series in Day-Ahead Market Contracts

Time series of risk premia in day-ahead market contracts for selected hours on working days. Sample period: September 25, 2006 to June 30, 2010. Hour 6 (5-6 am), hour 12 (11-12 am), hour 18 (5-6 pm), and hour 24 (11-12 pm) are displayed. The vertical axis is set between -50 and +50 Euro.
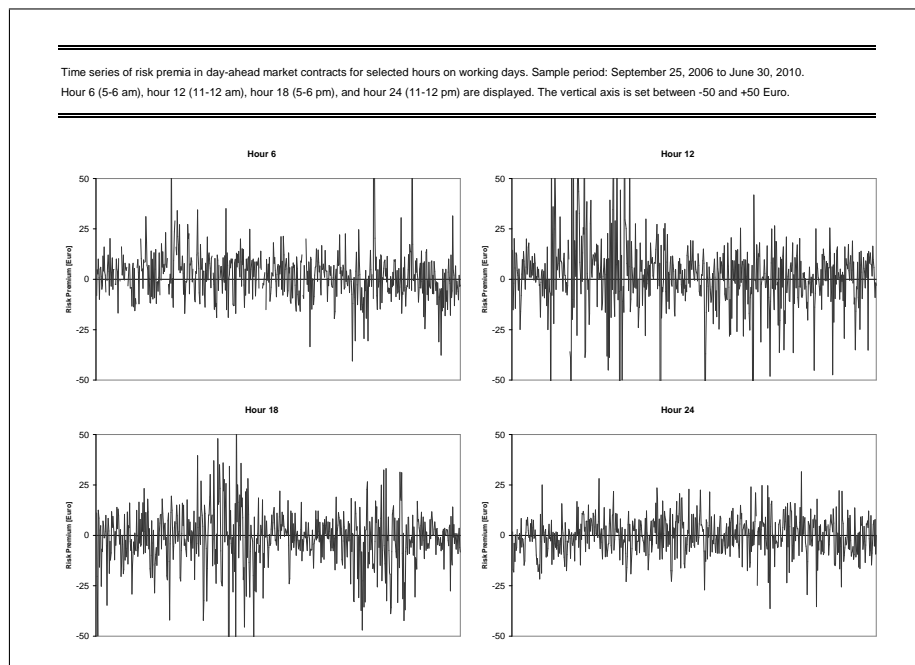
Source: Own work, based on Pietz (2009*b*).

graphs in figure 4.15 are set between minus and plus 50 Euro to amplify the different volatility. The last price in the corresponding intraday market contract is used to compute the data. As it can be seen, the risk premia time series for hour 12 and hour 18 show a significantly higher volatility compared to the other two hour contracts. A form of volatility clustering can be observed in the risk premia.

Time Variation Risk Premia

Another interesting question regarding risk premia in electricity markets is time variation, i.e. the existence of seasonality and the existence of a trend in the observed magnitudes. Hadsell & Shawky (2007) report for the New York wholesale market high risk premia in winter and summer months, according to the yearly demand pattern. Lucia & Torro (2008) report seasonality in risk premia in week futures traded at the Nord Pool. For the analysis of the data regarding the existence of seasonality in the risk premia, I have the choice to either analyze all hour contracts separately or to use the daily average or some blocks of hours. The estimation of the daily risk premia – calculated as the daily price in the day-ahead market minus the daily price in the intraday market – and the estimation of the average monthly risk premia based on the daily results seem to be the most straightforward approach.

Table 4.14

Risk Premia in Day-Ahead Market Contracts by Delivery Month (Working Days)

Risk premia in day-ahead market contracts by delivery month. The estimated risk premia are shown for three blocks of hours on working days. ***, ** and * indicate significance at the 1%, 5% and 10% level; the Newey-West estimator is used to obtain robust standard errors.

	Base			Peak			Off-Peak		
	Mean	Median	Std.Dev.	Mean	Median	Std.Dev.	Mean	Median	Std.Dev.
January	-2.49***	-0.85	15.49	-4.3***	-1.82	18.14	-0.61	0.00	11.66
February	0.01	0.71	14.26	-0.82	0.54	16.17	0.73	0.24	10.96
March	0.15	0.02	11.72	-0.01	0.14	10.93	0.32	-0.19	12.54
April	0.63	0.99	13.11	0.83	1.59	15.36	0.42	0.42	9.95
May	-2.6***	-0.04	12.49	-2.25***	0.04	13.21	-2.95***	-0.43	11.62
June	0.06	0.24	14.70	-0.07	0.55	17.78	0.2	0.00	10.24
July	1.71***	2.88	14.03	-0.1	2.40	17.14	3.56***	3.48	9.27
August	0.44	1.03	11.14	-1.04*	0.50	11.92	1.96***	1.62	10.10
September	1.32***	0.97	13.89	0.57	0.51	16.34	2.08***	1.53	10.56
October	-0.31	-1.25	19.73	-0.14	-1.89	23.01	-0.5	-0.84	15.09
November	0.09	0.08	60.95	-3***	-0.05	81.22	3.24***	0.82	19.69
December	1.1'**	0.99	20.83	0.92	0.89	25.82	1.29**	1.11	12.44

Source: Own work, based on Pietz (2009*b*).

However, this procedure is not practicable due to the significant number of hours without trading in the intraday market.[48] I decide to evaluate the existence of seasonality by applying the following procedure: first, I estimate the risk premia in all hour contracts. Second, I reorder the estimated risk premia by months. Third, I calculate the average risk premia for three blocks of hours: base (0 – 24 am), peak (8 am – 8 pm) and off- peak (0 am – 8 am and 8 pm – 0 am); the choice of this blocks is based on the results obtained above which show that these hour blocks exhibit similar characteristics. Table 4.14 and table 4.15 summarize the results.

Significant positive risk premia on working days are found for summer months; regarding the base block, contracts with delivery in July and September exhibit statistically significant risk premia. Significant negative risk premia are found for January and May. The results for the other months are mixed and not significant. Carefully interpreting the results and taking into account the short sample, the existence of a seasonality in the risk premia in the spot market cannot be detected. This is confirmed by the results for non-working days in table 4.15. In contrary, Viehmann (2009) analyzes four selected hours and finds – using data from the day-ahead market and OTC prices – significantly higher risk premia in winter months.

Finally, I pose the question whether the risk premia changed over the last years. The question is whether the sign or magnitude of the risk premia are constant or evolve

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[48]Off-peak hours have the highest number of days without trading. It may be hence assumed that the daily average price is upward biased.

Table 4.15

Risk Premia in Day-Ahead Market Contracts by Delivery Month (Non-Working Days)

Risk premia in day-ahead market contracts by delivery month. The estimated risk premia are shown for three blocks of hours on non-working days. ***, ** and * indicate significance at the 1%, 5% and 10% level; the Newey-West estimator is used to obtain robust standard errors.

	Base			Peak			Off-Peak		
	Mean	Median	Std.Dev.	Mean	Median	Std.Dev.	Mean	Median	Std.Dev.
January	-1.38***	-0.53	12.97	-0.65	0.29	13.52	-2.12***	-1.42	12.35
February	0.45	1.46	12.71	-1.2	0.08	12.79	2.15***	2.58	12.41
March	0.84*	0.74	12.34	0.32	0.34	10.47	1.38*	1.16	14.02
April	2.04***	2.11	10.92	2.85***	3.16	10.49	1.2	0.38	11.30
May	1.1***	0.66	10.63	2.16***	1.90	9.27	0.01	-0.44	11.77
June	0.15	0.65	10.51	0.99*	1.11	9.25	-0.7	0.30	11.60
July	0.1	0.07	9.20	-0.15	-0.46	8.01	0.36	0.53	10.30
August	3.8***	3.09	12.67	4.71***	4.26	11.57	2.86***	2.07	13.69
September	2.38***	1.04	11.95	3.77***	2.09	11.49	0.94	-0.99	12.27
October	13.95***	3.13	103.29	8.23**	3.30	59.51	19.87**	3.11	134.25
November	-1.77**	-1.28	13.34	-3.36***	-1.95	13.70	-0.16	-0.33	12.79
December	4.94***	2.93	21.85	4.19***	3.12	17.50	5.75***	2.74	25.75

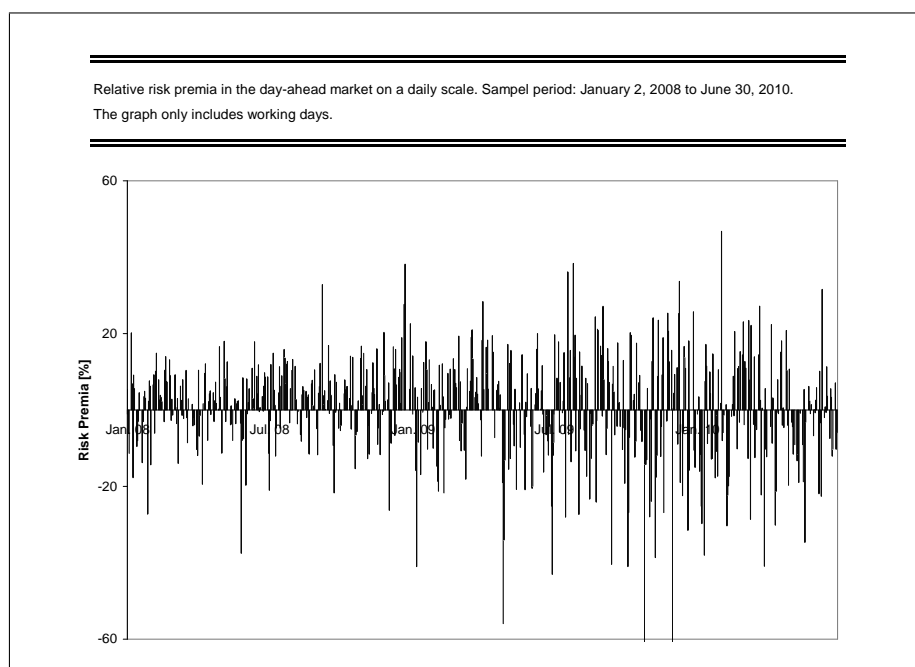**Source: Own work, based on Pietz (2009b).**

over time. To answer this question I decide to analyze the daily risk premia in the day-ahead market. These premia are calculated as the average of the 24 hourly risk premia. In the case that no trading in one of the hour contracts in the intraday market occurred, the daily risk premia is calculated with less than 24 values. The resulting time series is displayed in figure 4.16.

The y-axis in figure 4.16 is set between minus 60 and 60 Euro. The application of various simple methods to estimate whether a time evolution of the risk premia takes place yields no clear results. This is probably due to the high volatility at the end of the sample period after a strong increase over the last two years. Further research on the evolution of the risk premia is necessary[49], given an extended dataset is available.[50]

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[49]When testing for the evolution of the risk premia throughout the analyzed sample period, I find no obvious trend. From beginning on the risk premia seem to be positive and extremely volatile. The negative daily risk premia obtained by Daskalakis & Markellos (2009) for the first year of the intraday market's existence are probably due to calculation of daily prices on the intraday market as arithmetic averages of the hourly prices and the high number of non-trading hours in this period.

[50]Similar to Boogert & Dupont (2005) I examine the practical relevance of the hourly risk premia by testing two simple (spread) trading strategies over the period August 2008 to May 2009. A spread strategy in electricity markets consists of a long position in one market segment and a short position in the other one. Therefore, I examine the two hours with the largest positive and negative risk premia over the whole sample period (on working days), hour 9 and hour 12. For the hour with a positive risk premium the strategy to be tested is a short position in the day-ahead and a long position in the intraday market. For the hour with a negative risk premium the opposite strategy applies. The profit for the first strategy (per MWh) is the day-ahead price minus the intraday price, for the second strategy the intraday minus the day-ahead price. I start the test in August 2008, because from this month on there is no occurrence of non-trading days in the hours of interest.

Figure 4.16
Time Variation Daily Risk Premia Day-Ahead Market

Relative risk premia in the day-ahead market on a daily scale. Sampel period: January 2, 2008 to June 30, 2010. The graph only includes working days.

Source: Own work.

Term Structure of Risk Premia

The time period between September 25, 2006 and August 30, 2008 offers the unique opportunity to analyze the German electricity spot market in respect to the existence of a term structure of risk premia. That is due to the fact that during this time period the three market segments were simultaneously in existence. Thus, it was possible to buy and sell electricity for the same delivery period in three different market segments with the only difference being the trading point-in-time or rather the time-to-delivery of the specific contract. However, it was not possible to trade electricity contracts with delivery in every individual hour. Rather the tradable delivery periods were determined by the block contract market. The tradable delivery periods were hence the whole day (base load contract), the peak hours (peak load contract), and

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Without further investigating the traded volume (and by ignoring transaction costs) I assume that it is possible to trade an additional volume of 10% at the quoted price in the intraday market. As results I get a three-digit average profit for hour 9 and a three-digit average loss for hour 12 as well as a high volatility. Based on these results I wonder whether professional market participants with no interest in the physical delivery of electricity (speculators, arbitrageurs, etc.) are seriously interested in investing time and money in trading strategies with such profit-loss potentials. Discussing this point with representatives of a leading investment bank in Western Europe I received the argument that based on the low liquidity in the intraday market and on the high volatility of the risk premia the potential profits of an arbitrage strategy based on the risk premia are by far not sufficient to justify an engagement.

the off-peak hours (through a synthetic contract: a long position in the base load contract and a short position in the peak load contract).

For the analysis of the term structure, I relax the restriction to the intraday market data. Otherwise, the sample period with overlapping trading in the three market segments would be only eight months. However, the obtained results have to be interpreted with caution as the liquidity during parts of the sample period was extremely low.

The question whether market participants are willing to pay different risk premia depending on the time-to-delivery is of high importance, for both theoretical and empirical purposes. The results above indicate that similar to other markets the German spot market is characterized by positive risk premia. However, based on the above results no conclusion concerning a term structure of risk premia can be drawn. Empirical results on the existence of a term structure of risk premia in futures markets are mixed. Shawky et al. (2003) find that the risk premia in futures with delivery at the California-Oregon Border, traded at the New York Mercantile Exchange, are an increasing function of time-to-delivery. Weron (2008) and Marckhoff (2009) on the other side offer empirical evidence for a decreasing risk premia with increasing time-to-delivery. From a theoretical point of view, the framework developed by Benth et al. (2008) is able to explain a term structure of risk premia with changing risk preferences and hedging demand across different maturities. All empirical results obtained to date deal with maturities in the range of weeks or months. To my best knowledge, I am the first to have the possibility to research the term structure of risk premia on such a short time scale. The already obtained results lead to the expectation to find higher risk premia in the block contract market.

When analyzing the available data the low liquidity in the block contract and in the intraday market has to be considered. In particular at the beginning of the sample period defined above, when trading in the intraday market had just been introduced and at the end, when trading in the block contract market was coming to an end. For this reason, I reorder the dataset. For the analysis of a specific contract only days with trading in all hours of interest in all three market segments can be included in the final dataset. Originally, the sample period extends to over 706 trading days, 486 of them being working days.

I begin to reorder the data with the working days. The reduction of the dataset to days when trading in all hours of interest in the intraday market took place, results in 174 working days with trading in all hours and 350 working days with trading in the peak hours. In a second step, I sort out all days without trading in the corresponding block contract. I get 147 working days for the base hours and 285 working days for the peak hours at which at least one trade in all three market

Table 4.16
Term Structure of Risk Premia

Term strucutre of risk premia. The risk premia are estimated with the last price on the intraday market on working days. ***, ** and * indicate significance at the 1%, 5% and 10% level; the Newey-West estimator is used in order to obtain robust standard errors.

	Block Contracts			Day-Ahead Contracts		
	Mean	Median	Std.Dev.	Mean	Median	Std.Dev.
Base	1.60	1.62	11.63	0.42	1.16	9.47
Peak	3,04***	1.92	18.10	1,76**	1.04	15.17
Off-Peak	0.07	0.55	6.73	0.33	0.37	5.36

Source: Own work, based on Pietz (2009*b*).

segments and hours of interest took place. For the off-peak hour contracts trading in all off-peak hours in the intraday market and in both the peak and the block contract in the block contracts market is necessary. The reordering shows that this has been the case on 132 working days. Conducting the same reordering procedure for the non-working days results in an extremely small dataset. Therefore, I decide to forgo the non-working days. Thus, the following analysis only deals with working days.

After the reordering of the data, I estimate the risk premia at two points-of-time, one being the trading in the block contract market and the other one in the day-ahead market. This results in the estimation of two risk premia in contracts with identical delivery periods and different time-to-deliveries. The results allow me to evaluate whether a term structure of risk premia on such a short time scale is apparent. The results for the two markets and three contracts are shown in table 4.16.

Due to the skewness of the distributions of the risk premia table 4.16 contains the average and the median risk premia. I again employ the last price from the intraday market. The risk premia in the block and in the day-ahead market contracts are estimated as the price difference between the particular market and the intraday market. That is a significant difference compared to the section above, where the risk premia in the block contracts were estimated as the price difference between the block contract and the day-ahead market. The results for the base and off-peak hours are insignificant although in the off-peak hours the risk premia seem to be higher in the day-ahead than in the block contracts. The risk premia are higher in the block contracts for the base hours than in the day-ahead contracts. For the peak contracts – as mentioned the most liquid ones – I get statistically significant results. The risk premium in the peak load contract is on average 3.04 Euro and significant

at the 1% level. For the day-ahead peak hours I get a risk premium of 1.76 Euro, significant at the 5% level.

Market participants were apparently willing to pay a higher risk premium for the possibility of an earlier hedge during the period when all three market segments of the spot market were active. For the peak hours, for example, the risk premia in the block contracts are around 70% higher than for the day-ahead market contracts. This results are in accordance with the findings above.

Drivers of Risk Premia

When investigating potential drivers of the risk premia the equilibrium model of Bessembinder & Lemmon (2002) provides a relation between the anticipated distribution of the expected spot price and the ex ante risk premium. It identifies the third and fourth moment of the price distributions as determinants of the risk premia. With the methodology proposed by Longstaff & Wang (2004), this theoretical model can be transformed into an empirically testable relation. The ex post risk premia $\pi_i(T)$ are regressed on the variance, $VAR_i[S(T)]$, and skewness, $SKEW_i[S(T)]$, of the corresponding spot prices in this analysis. The skewness in this case is non-standardized. The relation is defined as

$$\pi_i(T) = a + b \cdot VAR_i[S(T)] + c \cdot SKEW_i[S(T)]. \tag{4.8}$$

Bessembinder & Lemmon (2002) show that the relation between the risk premia and the variance – under certain conditions – is negative and between the risk premia and the skewness positive.

I regress the 24 hourly ex post risk premia in day-ahead market contracts on the variance and skewness of the corresponding price distributions, for both working and non-working days, and find no significant results for the coefficients. Thus, I do not report the results.

These findings are contrary to Longstaff & Wang (2004) who find a significant relation for the PJM day-ahead market. To my best knowledge Ronn & Wimschulte (2009) are the only ones testing the relation for the German spot market. They use the risk premia in futures traded at the Austrian exchange with delivery in Germany and the prices in the day-ahead market of the EEX. The authors distinguish also between working and non-working days. The results for working days are all insignificant, for non-working days only the relation for the risk premia on Sundays are found to be significant.

Table 4.17

Risk Premia in Month Base Futures

Risk premia in month base futures. The risk premia are calculated with monthly data. ***, ** and * indicate significance at the 1%, 5% and 10% level; the Newey-West estimator was used in order to obtain robust standard errors.

	Absolute Risk Premia			Relative Risk Premia		
Maturity	Mean	t-value	Std.Dev.	Mean	t-value	Std.Dev.
One	2.16**	2.11	8.53	3.42	1.59	18.23
Two	2.83*	1.78	11.10	3.57	1.15	22.70
Three	3.15	1.57	12.34	3.67	0.97	23.97
Four	3.15	1.35	13.45	3.22	0.75	25.17
Five	3.2	1.22	14.68	2.58	0.55	26.71
Six	3.09	1.10	15.53	1.74	0.34	28.48

Source: Own work, based on Pietz (2009a).

4.4.3.2 Risk Premia in Futures Contracts

The results for the futures market are reported in four parts. First, the estimated risk premia are reported. Afterwards, the potential term structure of risk premia is discussed and then the time-dependence is analyzed. Finally, potential drivers are addressed.

Risk Premia in the Futures Market

Using the monthly spot prices which were shown in figure 4.10, I estimate the risk premia in the month futures. The estimation follows equation (4.2) for the absolute risk premium and equation (4.7) for the relative risk premium. The futures prices are aggregated to monthly prices to overcome autocorrelation problems. The aggregation of the data results in a shortening of the time series for every futures contract from approximately 150 observations to six monthly prices. Every monthly price is used for the computation of the risk premium with corresponding time-to-delivery.[51]

The results are reported in tables 4.17 and 4.18 for the base and peak futures, respectively. Standard errors are calculated autocorrelation and heteroscedasticity robust using the Newly-West estimator. The standard deviation and the t-value are reported as well.

The absolute risk premia exhibit a similar evolution for both the base and peak futures. A steadily increase with the time-to-delivery is observed. When the risk premium in the one month base futures accounts to 2.16 Euro, the risk premium in the six month futures is with 3.09 Euro approximately 45% higher. For the peak

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[51]All estimations are also performed on the daily data. The results are similar to the results on monthly data except lower standard errors due to the autocorrelation.

Table 4.18

Risk Premia in Month Peak Futures

Risk premia in month base futures. The risk premia are calculated with monthly data. ***, ** and * indicate significance at the 1%, 5% and 10% level; the Newey-West estimator was used in order to obtain robust standard errors.

Maturity	Absolute Risk Premia			Relative Risk Premia		
	Mean	t-value	Std.Dev.	Mean	t-value	Std.Dev.
One	4.06**	2.29	15.70	4.81*	1.85	23.26
Two	5.62**	2.13	19.71	5.57	1.54	28.13
Three	6.16**	1.93	20.96	5.97	1.41	28.78
Four	6.24*	1.74	21.80	6	1.29	28.96
Five	6.54	1.66	22.95	5.99	1.18	29.91
Six	6.54	1.54	24.33	5.31	0.95	6.00

Source: Own work, based on Pietz (2009a).

futures the risk premium in the one month futures accounts to 4.06 Euro and for the six month futures to 6.54 Euro; the increase is approximately 60%. However, a look at the relative risk premia questions this monotone increase. Here the risk premia in the base futures reach a maximum in the third month futures and decrease afterwards. In the peak futures the maximum is observed in the four month futures.

Regarding the statistical reliability of the results, the risk premia in the one and two month base futures are significant. For the peak futures the risk premia in the one to four month futures are found to be significant. The significance of the relative risk premia is weak; only the risk premium in the one month peak futures is significant.
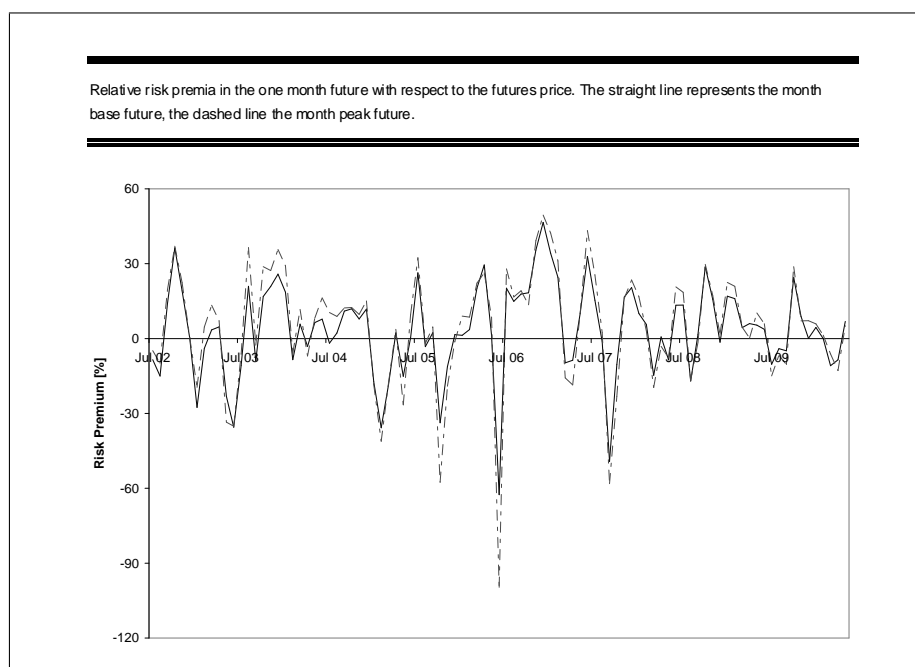
The obtained significant results for the risk premia confirm the hypothesis that electricity consumers seem to mainly use short-term futures for hedging purposes. The evidence for decreasing risk premia in futures with longer time-to-delivery is in accordance with the theory as well; a decreasing demand of the electricity consumer could results in a decrease of the hedging pressure together with the risk premia. Thus, a term structure of risk premia could exist in the German market in accordance with the theoretical predictions with the model of Benth et al. (2008).

The estimated relative risk premium accounts for around 3% of the price of the one month base futures and for around 5% of the month peak futures. Compared to other futures markets, this is a relatively large risk premium which the market participants are seemingly willing to pay for the disposal of price risk for a time horizon of one month.

To analyze the time evolution of the risk premia, figure 4.17 shows the relative risk premium in the one month base and peak futures over the sample period.

Figure 4.17 reveals that the relative risk premia are highly volatile and change regu-

Figure 4.17
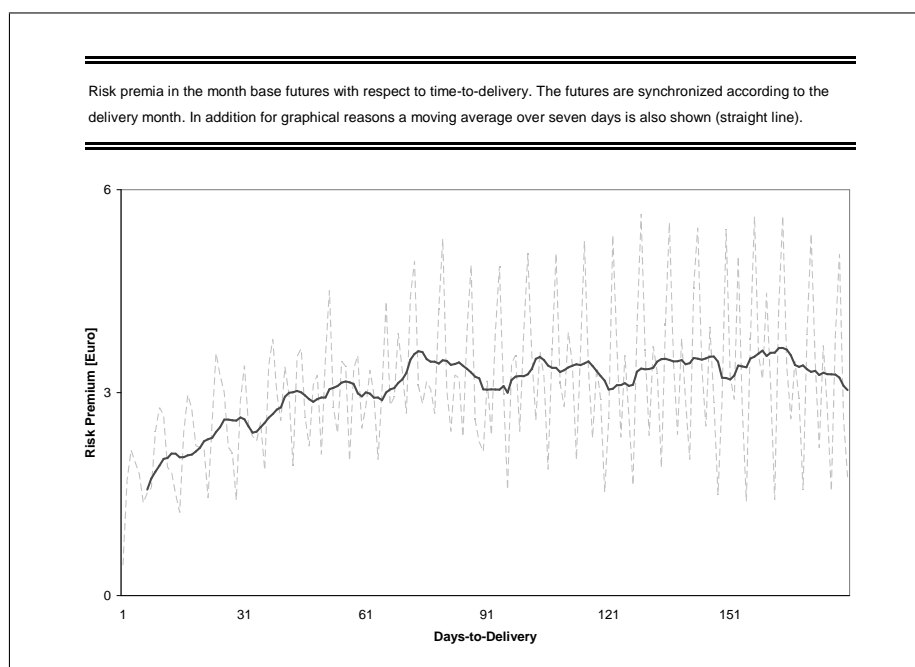Relative Risk Premia in One Month Futures

Relative risk premia in the one month future with respect to the futures price. The straight line represents the month base future, the dashed line the month peak future.

Source: Own work, based on Pietz (2009*a*).

larly in sign. However, tt can be assumed that large parts of these two effects are due to forecast errors. Theses errors result in partially dramatic discrepancies between futures and realized spot prices, in parts exceeding 50%. These discrepancies are by far greater than the estimated average risk premia which are in the range of 5%. Regarding the change in sign no systematic patterns are visible. The question whether the risk premia – both in sign and magnitude – evolve over time is hence difficult to answer. Further research needs to be done as a longer sample period is available since the evolution of risk premia over time is of high interest. The hypothesis is that the market entry of new market participants together with a learning curve should – at least from a theoretical point of view – lead to a more efficient market and hence to a decrease of the risk premia.

Term Structure of Risk Premia

The results in tables 4.17 and 4.18 provide evidence for the existence of a term structure of risk premia in the futures markets. I decide to analyze the daily data with the aim to find further support for a potential term structure. Therefore, I compute the absolute risk premia for every daily observation and synchronize the calculated risk premia according to the first day of the delivery month. This allows

Figure 4.18
Risk Premia in Month Base Futures by Time-to-Delivery

Risk premia in the month base futures with respect to time-to-delivery. The futures are synchronized according to the delivery month. In addition for graphical reasons a moving average over seven days is also shown (straight line).

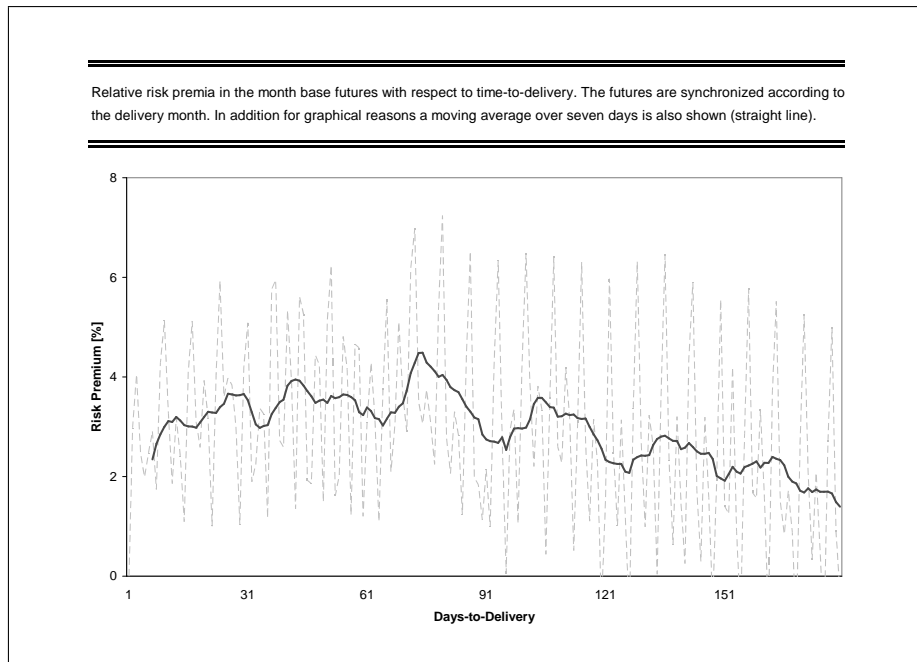**Source: Own work, based on Pietz (2009*a*).**

to sort all the obtained risk premia according to their time-to-delivery. The results of this computation are found in figure 4.18 for the six first month base futures.

The straight line in figure 4.18 is a moving average over seven days to smooth the daily risk premia data. This average is, in accordance with the results for the monthly data obtained above, increasing. An interpretation of this increase as a term structure of risk premia, i.e. increasing risk premia with increasing time-to-delivery may be postulated. However, absolute risk premia exhibit the problem that changes on the price level may bias the results. Thus, the use of the relative risk premia is probably more meaningful in this case. The results of the same computation as above for the relative risk premia are found in figures 4.19 and 4.20. The relative risk premia in the month base and month preak futures, respectively, and in dependence of the time-to-delivery are depicted in these figures.

In both figures every data point is calculated, similar to the absolute risk premia in figure 4.18, on average from 60 separate observations. For a better vizualisation also here a moving average over seven days is displayed.
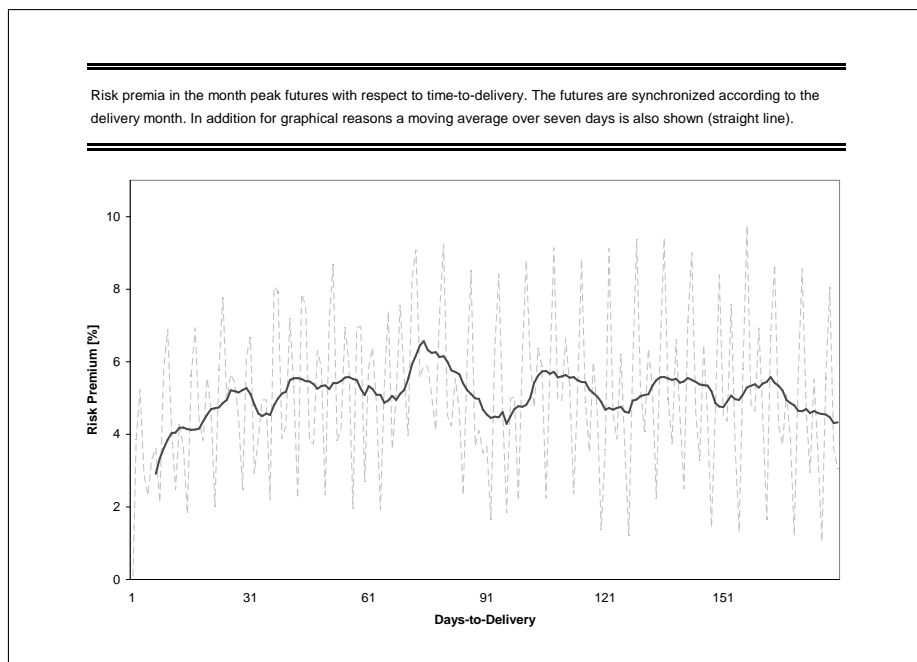
The results for the relative risk premia are different to the of the absolute risk premia. The relative risk premia in the base month futures, for example, indicate a term structure with an increasing or stable risk premium at the short-end and

Figure 4.19
Relative Risk Premia in Month Base Futures by Time-to-Delivery

Relative risk premia in the month base futures with respect to time-to-delivery. The futures are synchronized according to the delivery month. In addition for graphical reasons a moving average over seven days is also shown (straight line).

Source: Own work.

Figure 4.20
Relative Risk Premia in Month Peak Futures by Time-to-Delivery

Risk premia in the month peak futures with respect to time-to-delivery. The futures are synchronized according to the delivery month. In addition for graphical reasons a moving average over seven days is also shown (straight line).

Source: Own work.

then a decreasing risk premium with increasing time-to-delivery. Unfortunately, the dataset does not include long-term futures to test whether this trend is also observed for futures with longer time-to-delivery. The results for the peak futures are rather pointing to a flat term structure. However, a high volatility at the long-term is visible. These results are in accordance with the results for the spot market which were discussed in the last section. I find for the spot market an increasing risk premia at the short-end. When comparing this with figure 4.19 also in the futures market an increase at the short-end is found.
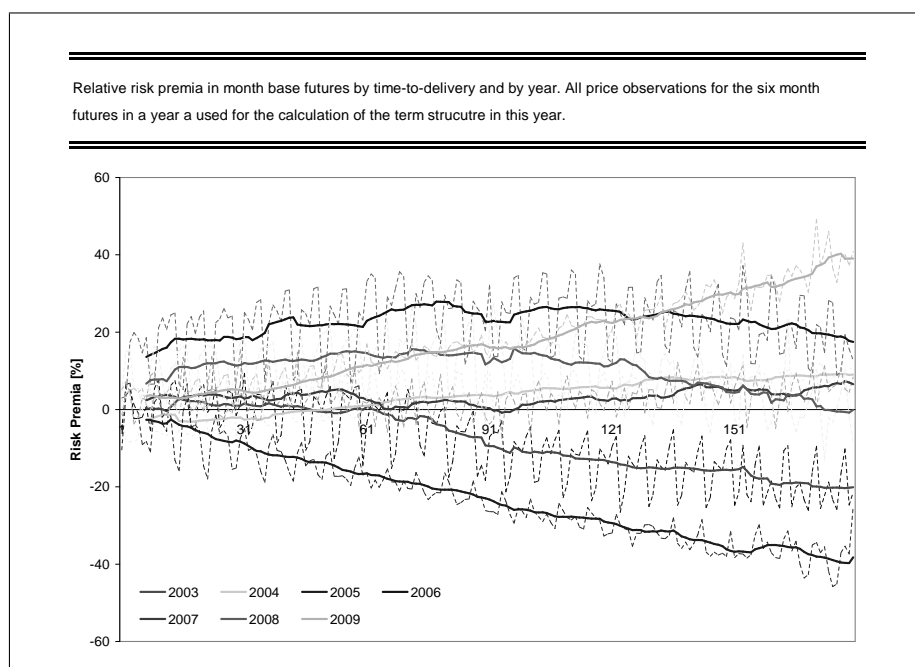
Shawky et al. (2003) were the first to report results on the relationship between risk premia and time-to-delivery. For the years 1998 and 1999 they find a linear increasing risk premium with increasing time-to-delivery for the California-Oregon Border area. On the other side, Diko et al. (2006) find positive short-term and negative long-term risk premia in OTC forward prices for three European futures markets. Decreasing risk premia with increasing time-to-delivery are reported by Marckhoff (2009) for the Nord Pool market. Weron (2008) finds the same effect by modeling the market price of risk for the Scandinavian area through stochastic models. Benth et al. (2008) develop a theoretical model to explain this effect.

Posing the question whether the risk premia is stable over the sample period, I calculate the term structure for every full year in the sample period. Therefore, I divide the data which were used for the estimation of the term structure above by years. I use the month base futures. A term structure for 2007, for example, is estimated with all price observations of the first six month futures in this year. The futures are again synchronized to the delivery month. The results of this procedure for the years 2003 to 2009 are shown in figure 4.21.

The results of the estimation on a yearly scale show that the term structure is not stable. In 2005, for example, almost perfect linearly decreasing risk premia with time-to-delivery are observed. In opposite, in 2009 almost perfectly increasing risk premia are found. In both cases the relative risk premia at the long-end of the term strucutre account to around 40% and -40%, respectively. The other years are between these two extreme cases. Except for 2008, where also significantly decreasing risk premia with increasing time-to-delivery are observed, the other yearly estimations reveal either an almost monotone term structure or an increase at the short-end and a decrease afterwards.

The results displayed in figure 4.21 pose the question on the stability of the aggregated risk premia in figures 4.19 and 4.20. Further research is necessary on this topic, but it seems that, based on the obtained results, a (stable) term structure of risk premia in the futures market has to be denied. Regarding the short-end, i.e. the one and two month futures, it seems possible to conclude that a positive risk premia

Figure 4.21
Relative Risk Premia in Month Base Futures by Year

Relative risk premia in month base futures by time-to-delivery and by year. All price observations for the six month futures in a year a used for the calculation of the term strucutre in this year.

Source: Own work.

is observed over the years. Regarding the long-end, on the other side, no conclusion can be drawn as the results are too mixed. However, it seems that for most of the time decreasing risk premia occur at the long-end.

Regarding future research, it is of interest whether it is possible to identify factors which determine the change in the risk premia at the long-term over the years. For example the possibility exists that trading strategies based on recently observed risk premia are responsible for the regular changes as market participants try to profit from the observed price differences.

Time Variation Risk Premia

The time variation in the occurrence of risk premia gained significant research in the last years. Lucia & Torro (2008), for example, find seasonality in the risk premia at the Nord Pool. Their results indicate that risk premia are highest and statistically significant for delivery periods in winter and zero for delivery periods in summer. Cartea & Villaplana (2008) model the magnitude and sign of risk premia depending on demand and capacity.[52] One implication of their model is the occurrence of positive risk premia which are caused by high volatility of demand. This implies positive

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[52]Cf. section 2.3.3.2 for a discussion of the model developed by Cartea & Villaplana (2008).

Table 4.19

Risk Premia in Month Base Futures by Delivery Period

Average risk premia in the analyzed individual month base future contracts which are observed over their whole trading period. ***, ** and * indicates significance at the 1%, 5% and 10% level; the Newey-West estimator was used in order to obtain robust standard errors.

FUTURE	2003	2004	2005	2006	2007	2008	2009	2010	AVERAGE
January	-0.8	8.34	6.85	-12.27	35.84	10.37	26.93	6,23	10.19
February	-6.74	9.49	-2.76	-12.7	32.99	8.02	30.72	6,91	8.24
March	-2.15	0.16	-11.09	-7.19	27.47	5.83	25.68	3,75	5.31
April	0.06	3.7	-7.65	7.25	9.47	-10.71	16.91	-0,49	2.32
May	0.42	0.28	-6.03	13.67	1.71	-2.58	10.04	-4,29	1.65
June	-6.45	2.48	-11.81	11.05	4.58	-12.71	8.05	-2,16	-0.87
July	-12.86	1.71	-8.33	-22.26	15.78	-1.31	6.05	-	-3.03
August	-7.7	-0.55	2.14	7.1	10.93	2.93	-1.71	-	1.87
September	-0.36	-0.5	-4.39	8.76	5.45	-15.24	-0.52	-	-0.97
October	-4.72	3.21	-2.13	11.11	-16.14	-6.97	-2.11	-	-2.54
November	1.72	6.32	-21.49	13.54	-14.02	25.73	13.23	-	3.58
December	3.7	5.09	-12.98	23.72	-0.93	28.06	10.21	-	8.13
AVERAGE	-2.99	3.31	-6.64	3.48	9.43	2.62	11.96	1.66	-

Source: Own work, based on Pietz (2009*a*).

risk premia in winter months for the most markets. The model of Bessembinder & Lemmon (2002) also suggests the existence of seasonality in risk premia is caused by demand uncertainty.

Due to the lack of a sufficient sample period, I cannot directly test for seasonality in the German futures market. I only have at maximum eight futures with delivery in a particular month, meaning that only eight independent expectation building processes regarding a particular calendar month took place. To overcome this problem, I calculate the average risk premia contained in every individual futures contract. However, I do not calculate the significance of these individual risk premia as the price time series of an individual futures is highly autocorrelated. Thus, the price difference between the futures price time series and the spot price in the delivery month is almost always highly significant. However, this significance is probably in large parts due to forecast errors rather than to the systematic occurrence of risk premia. This point of view is supported by the change in sign of the risk premium which cannot be explained solely based on risk consideration arguments.[53] Price shocks with asymmetrical impact on spot and futures prices are one explanation for these forecast errors. The results for the base futures are reported in table 4.19.

As expected the calculated risk premia exhibit a high variability both in magnitude and sign. Therefore, I report the average for every particular month in the last

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[53]Cf. Redl et al. (2009), p. 362.

Table 4.20

Risk Premia in Month Peak Futures by Delivery Period

Average risk premia in the analyzed individual month peak future contracts which are observed over their whole trading period. ***, ** and * indicates significance at the 1%, 5% and 10% level; the Newey-West estimator was used in order to obtain robust standard errors.

FUTURE	2003	2004	2005	2006	2007	2008	2009	2010	AVERAGE
January	-2.69	20.58	13.35	-23.59	53.14	17.77	41.76	13.59	16.74
February	-7.14	22.76	-1.19	-15.49	53.47	18.78	49.14	12.88	16.65
March	0	5.01	-14.6	-6.19	47.32	10.16	42.65	8.92	11.66
April	3.8	10.83	-6.88	12.71	15.19	-15.56	25.85	3.49	6.18
May	1.62	1.96	-4.72	17.94	1.62	-5.09	13.66	-5.6	2.67
June	-13.03	5.02	-19.51	17.79	3.21	-18.43	14.1	-2.13	-1.62
July	-21.85	5.84	-8.55	-61.18	31.79	6.04	12.14	-	-5.11
August	-12.08	4.54	5.59	14.76	26.2	12.13	-2.67	-	6.93
September	4.66	3.56	-4.27	12.9	14.95	-14.95	-1.31	-	2.22
October	-4.09	6.66	-1.67	18.14	-21.04	-10.11	-6.5	-	-2.66
November	9.35	11.22	-43.62	15.1	-30.14	35.48	19.7	-	2.44
December	10.36	10.18	-25.84	36.69	-3.57	40.69	14.9	-	11.92
AVERAGE	-2.59	9.01	-9.33	3.30	16.01	6.41	18.62	5.19	-

Source: Own work, based on Pietz (2009a).

column. I find evidence for seasonality when comparing the averages. Positive risk premia are observed in winter months, i.e. from December to February. After a decrease in spring and autumn the summer months seem to be characterized by negative risk premia. However, no statistical verification of these results is possible as the averages are calculated over a maximum of eight observations. The results are confirmed by similar results for the peak futures reported in table 4.20.

The obtained results seem to be in accordance with the empirical literature on electricity futures market. They confirm that high risk premia tend to occur in winter months, in the German market in particular in the period December to February. On the other side, the risk premia in the summer months are significantly lower and oscillate around zero.

Drivers of Risk Premia

The results in the previous section provide evidence for the existence of risk premia in the German electricity futures market. This section is dedicated to the discussion of potential drivers. The analysis focuses on the question whether the existence of risk premia can be linked to risk considerations. Possible fundamental drivers are discussed qualitatively. The quantitative verification is left for further research.

I test the adequacy of the Bessembinder & Lemmon (2002) model as a potential

Table 4.21

Regression Risk Premia on Variance and Skewness of Underlying Spot Price

Regression of risk premia on variance and skewness of spot prices in the delivery month. The skewness is unnormalized. ***, ** and * indicate significance at the 1%, 5% and 10% level; the Newey-West estimator was used in order to obtain robust standard errors.

Future	a	b	c	Adj. R² [%]
Base	2.62***	-0.005509	-0.000024	21.75
Peak	10.34***	-0.002632	-0.000006	19.39

Source: Own work, based on Pietz (2009*a*).

explanation of the observed risk premia. Therefore, I regress according to equation (4.8) both the month base and the month peak futures prices on the third and the fourth moment of the spot price distributions in the delivery month. Performing this regression with monthly averages of the futures prices results in residuals with strong serial correlation. This is also observed by Redl et al. (2009); the authors hence use instead the futures price on the last trading day.[54] I decide to run the regression in the same way as Redl et al. (2009) and observe that the serial correlation problem is solved trough the replacement of the futures prices. However, the analysis is only performed for the one month futures as in the case of futures with a longer time-to-delivery the serial correlation is still present. The results of the regression are reported in table 4.21.

The coefficients for the variance and skewness reported in table 4.21 are not significant. Thus, the results do not support the Bessembinder & Lemmon (2002) model; the assumption that risk premia in the German electricity futures market are linked to risk considerations is not supported by this analysis.

Redl et al. (2009) analyze the one month futures in the period November 2003 to May 2008 and find mixed results. Regarding the futures markets in other countries, Furio & Lucia (2009), for example, analyze the Spanish futures market and find supporting evidence. Lucia & Torro (2008) report mixed results for the Nord Pool futures where the dependence holds before a shock period and thereafter vanishes. Marckhoff (2009) finds support for the model using data from the Nord Pool futures market. The mixed results reported in the literature suggest that other drivers may be relevant as well.

Fundamental factors can also serve as drivers of the risk premia. Only a few results have been reported to date. Douglas & Popova (2008), for example, link risk premia

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[54]However, the methodology of Redl et al. (2009) is still different as the authors use the variance and skewness of the spot price in the trading month for their analysis.

and gas storage inventories. The authors develop a model which links increasing gas storage inventories under realistic assumptions to a decrease of the risk premia. That is explained by a decreasing probability for the occurrence of price spikes. Daskalakis & Markellos (2009) link risk premia and emission allowance spot prices. They empirically demonstrate a positive relationship, among others with data from the EEX.

4.5 Concluding Remarks and Future Research

An empirical analysis of the German electricity wholesale market is conducted in this chapter. I aim to test the suitability of the risk premia approach as a price formation mechanism. Therefore, I conduct an in-depth analysis of the German market to detect the existence of potential risk premia. I apply the ex post approach. The analysis is divided in two parts: in the first part the focus is on the spot market, while in the second part I focus on the futures market.

In the first part, I analyze all three market segments of the spot market which are or were in existence during the sample period which extends between August 2002 and June 2010. These three market segments are the day-ahead market, the block contract market, and the intraday market. Trading in the day-ahead market in its current form started in August 2002, while trading in the intraday market started in September 2006. The block contract market ceased its activity in August 2008.

The analysis of the spot market yields the following results: I find positive risk premia in the block contract and in the day-ahead market. Risk premia in block contracts are particularly significant and high for contracts with delivery on Mondays. These contracts were traded on Friday and hence had a time-to-delivery of three days. Risk premia in day-ahead market contracts are extremely volatile and change in sign throughout the day. The average daily risk premium for non-working days is significant. Furthermore, I detect a term structure of risk premia during the sample period when all three market segments were active. Risk premia seem to be higher in contracts with a longer time-to-delivery. In addition, I examine potential time variation in the risk premia but find no significant results. Also the results for a potential seasonality are mixed. When testing for a relation between the variance and skewness of the underlying spot price and the risk premia, a relation proposed by Bessembinder & Lemmon (2002), I find no significant results.

In the second part, I conduct an analysis of the futures market. Because of liquidity considerations, I restrict the analysis to month futures with financial settlement. The sample period extends from July 2002 to June 2010.

The analysis of the futures market yields the following results: I find evidence for positive risk premia in short-term futures, i.e. futures with a time-to-delivery up to around three months, which are statistically significant. I also detect evidence for seasonality in the risk premia. The risk premia seem to be positive for delivery months in winter and zero or even negative in summer. When testing the existence of a term structure the results are mixed. It seems that in certain periods the risk premia increase with increasing time-to-delivery, wheras in other periods they decrease. However, the evidence indicates that the aggregate risk premia decrease in the long-term. The results for a verification of the Bessembinder & Lemmon (2002) model are negative.

The obtained results are consistent with both theoretical and empirical literature. They support the hypothesis that hedging pressure is an appropriate approach for price formation in the German electricity futures market. The short-term futures seem to be mainly used by electricity consumers for hedging purposes. With increasing time-to-delivery the demand of electricity consumers seems to decrease. This results in low and statistically insignificant risk premia in the mid-term and long-term futures. The question whether the risk premia change sign and thus whether a market segmentation is apparent cannot be answered due to the shortness of the sample period.

Further research on this topic seems to be promising and necessary. Regarding the analysis of the spot market an identification of potential drivers of the risk premia in the German market would extend the understanding of the price formation mechanism. In addition – as soon as a larger dataset is available – the time-variation of the risk premia should be analyzed. The question whether a convergence of the day-ahead and the intraday prices will take place or whether the risk premia will persist is of particular interest. Both research avenues are related to the question whether the observed positive risk premia are an appropriate compensation for the associated risk or rather an indication of market inefficiency. The liquidity of the intraday market needs to be further investigated in order to test the robustness of the results. An interesting research question is whether a relation between the magnitude of the risk premia and the liquidity exists. Regarding the analysis of the futures market, future research in at least two directions seems to be promising. First, the time-evolution of the risk premia in this market segment is of even higher interest than that in the spot market. As the main part of the liquidity in the German electricity market is found in this market segment, it should also be the market with the highest efficiency. To extend the used dataset the quarter and year futures could also be included when a sufficient liquidity and length of the time series is reached. Furthermore, when investigating the time evolution of the magnitude and sign of the

risk premia, the question on a constant average risk aversion could be posed. Second, an identification of fundamental drivers for the risk premia seems to be promising. The role of fuels (coal, gas, and oil) and of emission allowances is here of particular interest. As a relation is found for other markets the question is whether similar mechanisms are valid in the German market. However, other determinants – due to the different generation technologies, certain determinants can be market-specific – could also be found for the German market.

Chapter 5

The Impact of Model Complexity on the Simulation Results

Every valuation process is based on a broad set of assumptions. Examples are assumptions regarding the input factors, the output factors, the relation between these factors, and the necessary forecast models. In the case of stochastic simulation, additional assumptions regarding the simulation procedure need to be taken. However, it is rarely known which of the assumptions are crucial for the accuracy of the valuation results. Therefore, the question posed in this chapter is regarding the impact of certain assumptions on the valuation results.

In this chapter I quantify the impact of model complexity on the valuation results. I identify two parameter categories which have a significant impact, namely the applied forecast models and the general simulation setup. I valuate a power plant venture which is financed via project finance to quantify the impact. However, the focus of the case study is not on the precise specification of a power plant project but solely on the estimation of the robustness of the valuation result in relation to certain changes in the assumptions. At the beginning, I first give an introduction to the case study, addressing the specifics of the project and the simplifying assumptions. I define a base case as a parameter combination used at the beginning of the valuation process. Later, I relax the assumptions and first vary the simulation parameters and then the applied forecast models. The critical parameters and forecast models are identified. I conclude the chapter with a summary of the results and an outline of promising avenues for future research.

This chapter aims to answer the following three key questions:

- What are the basics of a power plant venture financed via project finance and which simplifying assumptions are justified?

- What is the impact of certain assumptions regarding the general simulation setup on the valuation results, i.e. which parameters are crucial for the valuation?

- What is the impact of certain assumptions regarding the applied forecast models on the valuation results, i.e. which parameters are crucial for the valuation?

5.1 Research Question

In this chapter the PFVT is applied within a case study to determine the profitability of a coal power plant financed via project finance. The research question underlying the case study is the quantification of the impact of model complexity on the valuation results.

The valuation is performed both from the equity and the debt provider's point of view. As valuation results I consider two main outputs, namely the probability distribution of the expected NPV and the cumulative default probability. Therefore, the aimed variations in the input parameters are applied in the following for the calculation of the NPV distribution and of the expected cumulative default probability (ECDP).

I analyze the effect of model complexity on the NPV distribution and the (cumulative) default probability of the project. In all simulations I first use the base case defined in section 5.2.2. Then, in each step, one parameter is changed. I divide model complexity into two components: (i) the complexity of the simulation procedure and (ii) the complexity of the forecast models. The complexity of the simulation procedure is defined along three dimensions: the number of iterations, the time-resolution (which defines how often the cash flow is analyzed), and the valuation method for equity. To explore their restrictive effects on the simulation results, I vary these three components across several dimensions. For forecast complexity, I vary the volatility and the correlation forecast models. For volatility forecasts, I use (i) historical volatility and forecasts obtained from (ii) a GARCH (1,1), (iii) an E-GARCH as well as (iv) a GJR-model. Regarding correlations, I apply (i) no correlations, (ii) historical correlations and (iii) correlations obtained from a DCC model.

Figure 5.1 summarizes the different variations of the model complexity which are analyzed in the following.

Figure 5.1
Dimensions of Model Complexity
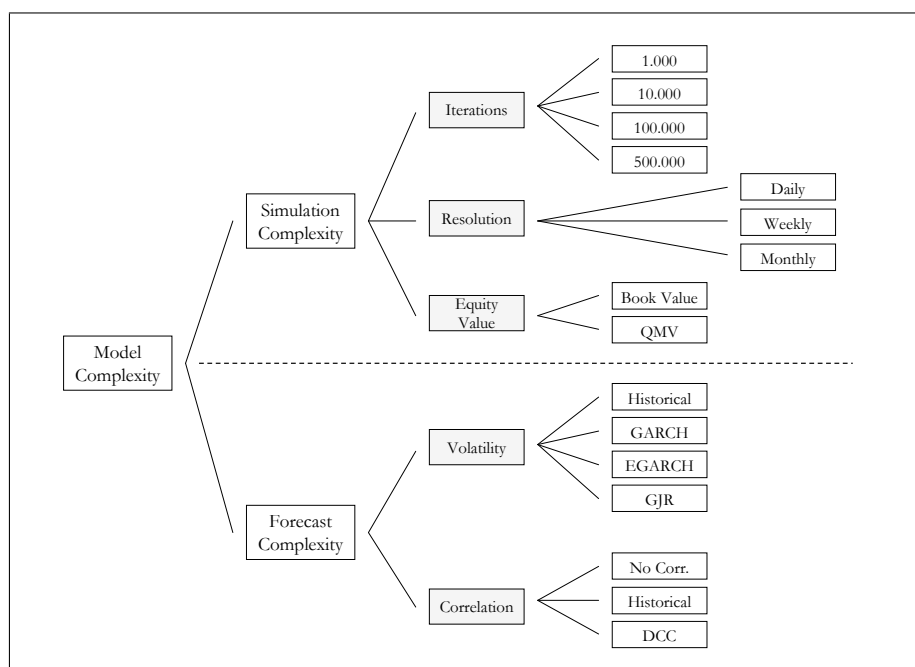
Source: Own work.

5.2 Case Study

5.2.1 Introduction

As a detailed consideration of all aspects of a real-life power plant project is beyond the scope of this chapter, I apply several simplifications to ease the specification of the project.[1] Since I am not focused on the (absolute) results for this certain project, but on the effects of model complexity, I expect these simplifications not to bias the results.

I assume that the coal power plant's construction takes place at one point-in-time, that the whole capital is immediately invested, and that the power plant is operated as a base load power plant. After the initial capital expenditure I identify four main types of relevant costs for the power plant project:

1. fixed costs: e.g. salaries, insurances,

2. variable costs: e.g. chemicals,

3. fuel costs: costs for coal, and

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[1]These assumptions are made due to simplification matters and are not necessary for the PFVT. The tool can handle very complex project structures.

4. costs for emission rights.

The power plant generates revenues which are dependent on the amount of electricity produced and the electricity price. The computation of the amount of electricity produced is not straightforward since several factors have to be taken into consideration. These factors are (i) capacity, (ii) load factor, (iii) operating time, and (iv) efficiency. To simplify matters, I assume that there is no technical improvement over the project's runtime; the efficiency of the power plant remains constant over the lifetime. Important factors affecting the project's cash flow are the price of electricity, the coal cost (coal input per MWh of electricity output), and the costs for emissions rights (costs per MWh of electricity output). These factors are the main drivers of the profitability of the power plant. As a detailed discussion of the underlying cash flow equation is already provided in the previous chapter I refer the interested reader to section 3.3.2.1.

I assume a capital requirement of 1 billion Euro as the initial investment for the build-up phase of the power plant. The financial structure in the case study corresponds to a typical project financed power plant. The debt-to-equity ratio at the beginning of the project is two[2] and the debt has a maturity of 20 years. Furthermore, I assume that one third of the debt is provided in U.S. Dollar and two thirds are provided in Euro. The runtime of the power plant is estimated at 40 years, with total depreciation to be reached after 20 years.

The whole FCFE is immediately distributed among the sponsors. An event of default generally occurs when the FCFE becomes negative, implying that the sponsors must re-invest cash in the project. However, this assumption would be very restrictive and not meaningful from an economic point of view. Thus, I assume that the sponsors have the obligation to re-invest money into the project up to a threshold of one third of their initial investments. Thereafter, every negative FCFE leads to an event of default of the project. The capital structure of the project and its cost of equity is permanently recalculated and adjusted during the simulated period of the project.[3]

Regarding the technical parameters of the power plant, an electricity generation capacity of 1000 MW, a load factor of 69% and an availability of 84% are assumed. Operating and maintenance costs are 5% of revenues plus 1 Euro for each generated MWh. Fixed costs, which include labor costs, are assumed at 5 million Euro per year. Regarding the relation between electricity output and fuel input I assume that 0.978 emission rights are necessary for each generated MWh of electricity. In

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[2]Cf. section 2.1.1.2 for a discussion of usually observed debt-to-equity ratios in project finance investments.

[3]Cf. section 3.3.2.4 for a discussion of the NPV calculation.

addition, the case study assumes 36% thermal efficiency for the generation process.[4]

Furthermore, I assume that sponsors taking an equity stake in project finance typically have a limited investment horizon of three to seven years.[5] By contrast, power plant projects have a runtime of 20 years and more. As a consequence, a sponsor must sell his stake in the project during its runtime. In order to do this, it is crucial for the sponsor to be able to determine the value of his stake at any point-in-time. The PFVT is able to simulate the project over its whole runtime. However, from an economic point of view, a simulation over such a long time period does not make much sense. To solve this issue, I model the project over a horizon of 5 years and assume that the whole project is sold to another investor afterwards. The selling price is calculated with the help of a valuation technique based on cash flow multiples, a method often applied in real-life project finance investments.

The starting point of the analysis is May 2009. As mentioned above, I model the first five years of the project's runtime based on the stochastic modeling of the cash flows. Afterwards, I assume that the project is sold for the price calculated using a multiple based valuation approach. As common for power plant valuations, I calculate its value as two times the average of its last three annualized free cash flows to equity.[6]

5.2.2 Base Case

For the beginning of the valuation process I define a base case, a parameter and forecast model setup used for the calculation of the first basic results. The following forecasting methods are used for the different influencing factors within the base case: I apply an ARMA(1,1) model for the electricity price, the emission rights, the interest rates and the U.S. Dollar / Euro exchange rate. For the coal price I use an ARMA(2,2) model.

The power plant is assumed to operate 24 hours and 7 days a week as it is natural for base load power plants. This allows the forecasting of electricity prices without consideration of their specifics, in particular their extreme intra-day and intra-week variation.[7] The reference price for electricity is the daily day-ahead market price from the EEX as this is the market segments with the highest market liquidity. Moreover, the use of futures prices is not possible as hedging is not yet implemented.[8] All price forecasts are based on the data analyzed in the previous chapter.

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[4]These assumptions are based on discussions with both practitioners and researchers. Furthermore data is taken from Wagner et al. (2004) and IEA (2010).
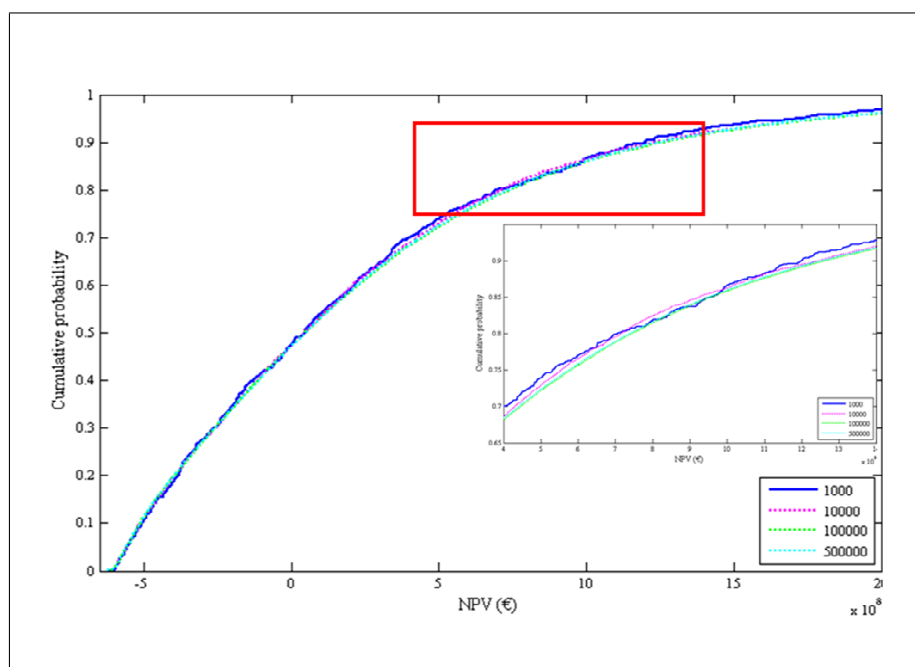
[5]This assumption is based on discussions with project finance investors.

[6]This assumption is based on discussions with project finance investors.

[7]Cf. chapter 4 for a discussion of the characteristics of electricity prices.

[8]It is intended to implement hedging and hence the use of futures prices in the near future.

Figure 5.2
Impact Number of Iterations on NPV

Source: Own work, based on Weber et al. (2010).

Further properties of the base case are:

1. all price forecasts are obtained based on ARMA-models[9],

2. volatilities forecasts are based on a GARCH (1,1) model,

3. future correlations are assumed to be equal to historical correlations,

4. the model's time resolution is weekly,

5. the calculation of the equity's market value is based on the QMV-method, and

6. the number of iterations is 100,000.

5.3 Case Study: Results

5.3.1 Impact of Simulation Complexity

The number of iterations is the first parameter to be analyzed. It is expected that an increase in this parameter leads to a smoother distribution function of the NPV.

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[9]I do not vary the price forecast models since their impact on the simulation outcome is obvious

Figure 5.3
Impact Number of Iterations on Default Probability
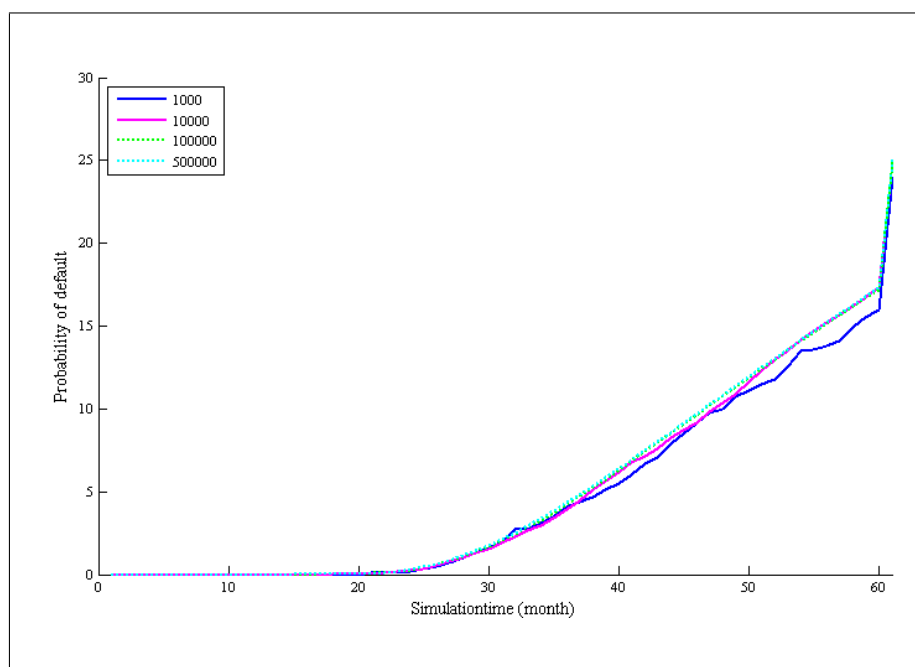
Source: Own work, based on Weber et al. (2010).

As expected, the level of the distribution function remains (largely) unchanged. Figure 5.2 presents the distribution function of simulations with different numbers of iterations. I simulate the project with 1,000, 10,000, 100,000, and 500,000 iterations. As expected, the number of iterations has no significant effect on the overall level since there is no systematic shift in the cumulative distribution function. However, for 1,000 and 10,000 iterations, the function is rather unsteady, as shown in the enlargement of figure 5.2. As a consequence, the expected NPV may be over- or underestimated, depending on whether the function is above or below its "true" value at a certain point. The application of at least 100,000 of iterations seems to be favorable. The step from 100,000 to 500,000 iterations does not increase the smoothness of the function significantly. I recommend using at least 100,000 iterations for a simulation to obtain smooth distribution functions. The same effects can be observed for the ECDP, which is reported in figure 5.3.

The drawback of an increased number of iterations is that the computation time rises significantly. As presented in figure 5.4, the computation time on the used system, a commercially available high-end personal computer, rises from 2 minutes for 1,000 iterations to 270 minutes for 500,000 iterations. Therefore, it is necessary to weight the advances of an increased number of iterations, a smoother distribution

Figure 5.4
Impact Number of Iterations on Computation Time
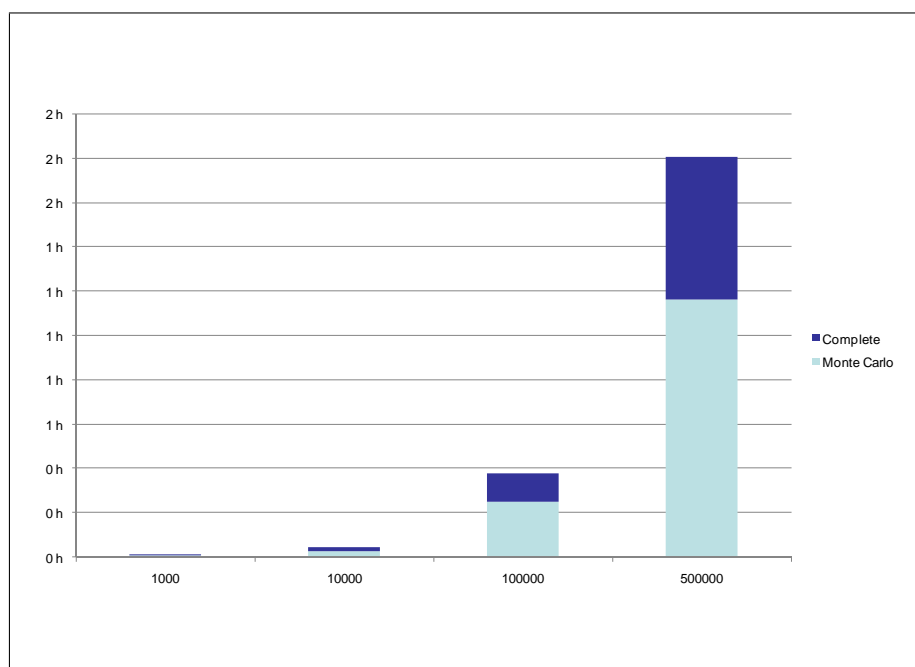
Source: Own work, based on Weber et al. (2010).

function, against its drawback in terms of more computation time. As mentioned before, an increase from 100,000 to 500,000 iterations does not lead to a strong improvement in smoothness, but to a five times higher computation time. However, below 100,000 iterations the distribution function is very rocky and not satisfying. As a consequence, the above proposed 100,000 iterations seem to be a good compromise between distributions smoothness and computation time.

Next, I analyze the impact of the applied equity valuation method on the simulation results. Figure 5.5 presents the two methods included in the PFVT, equity valuation based on QMV, and on book values.

I find that the cumulative distribution function differs for the two methods. The NPV distribution is narrower with less extreme values for the equity valuation based on book values compared to the QMV. The rationale behind this observation is that the application of equity book values leads to biased estimates of the cost of equity since they are not linked to the success of the project. In reality, the costs of equity depend on the success and, hence, on the risk of a project. Since book value estimation does not take this aspect into account, it overestimates the costs of equity for successful projects and underestimates them for unsuccessful projects. The QMV links the costs of equity to the profitability of a project to avoid this misjudgment. This estimation

Figure 5.5
Impact Equity Valuation Method on NPV
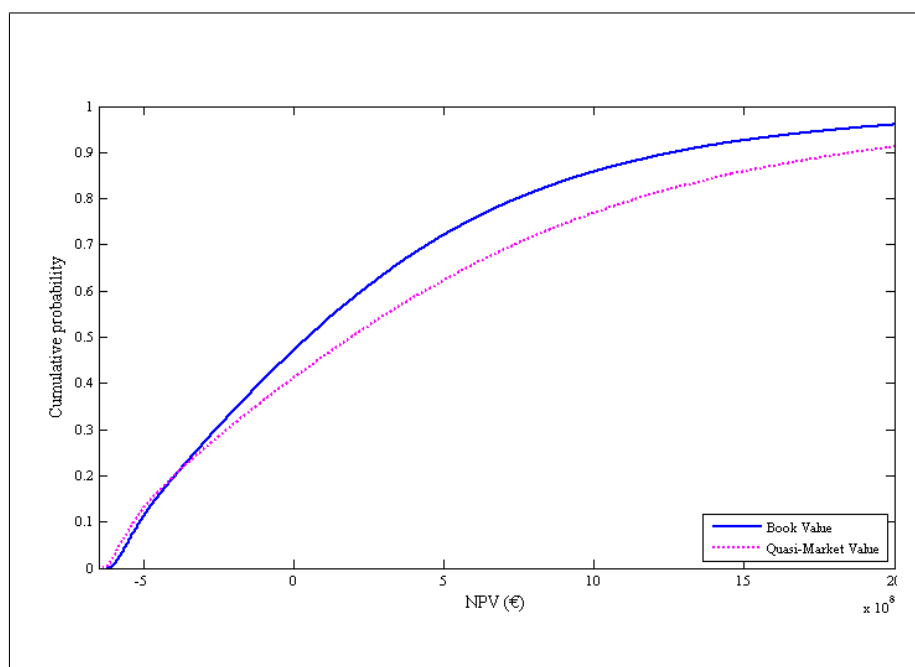
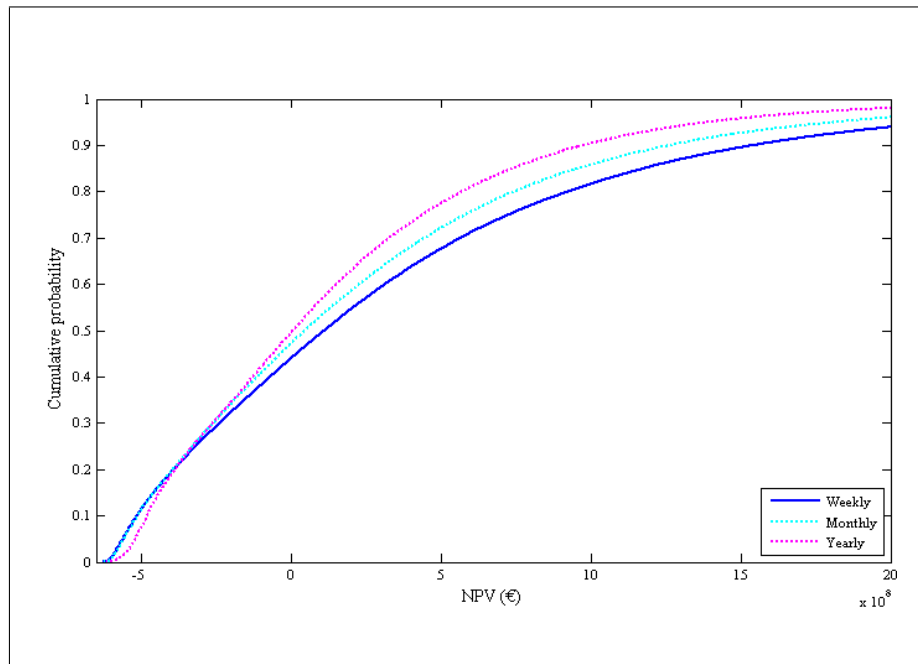**Source: Own work, based on Weber et al. (2010).**

on the one hand leads to more extremely high NPV estimates (because the discount rate for successful projects is smaller) and on the other hand to more extremely low NPV values (because the discount rate for unsuccessful projects is higher). This can be seen in the cumulative distribution function. The project's ECDP is not affected by the equity valuation method. Consequently, I do not report this figure.

The time resolution is another crucial parameter of the simulation. The time resolution defines how often the project's cash flow is analyzed. For example, a weekly time resolution means that the cash flow of the project is computed and analyzed each week during the simulation phase of the project. I analyze the impact of a weekly, monthly, and a yearly time resolution. Figure 5.6 presents the impact of the time resolution on the simulation results.

As it can be seen, a higher time resolution leads to a broader NPV distribution and to more large positive and negative events. The higher frequency of small (negative) NPV estimates is not surprising since a higher time resolution is accomplished by more default events as presented in figure 5.7.

Since the cash flow is more often analyzed with, for example, weekly resolution compared to yearly resolution, a stream of negative cash flows over several weeks may lead to a project default. These events of default do not necessarily happen

Figure 5.6
Impact Time Resolution on NPV

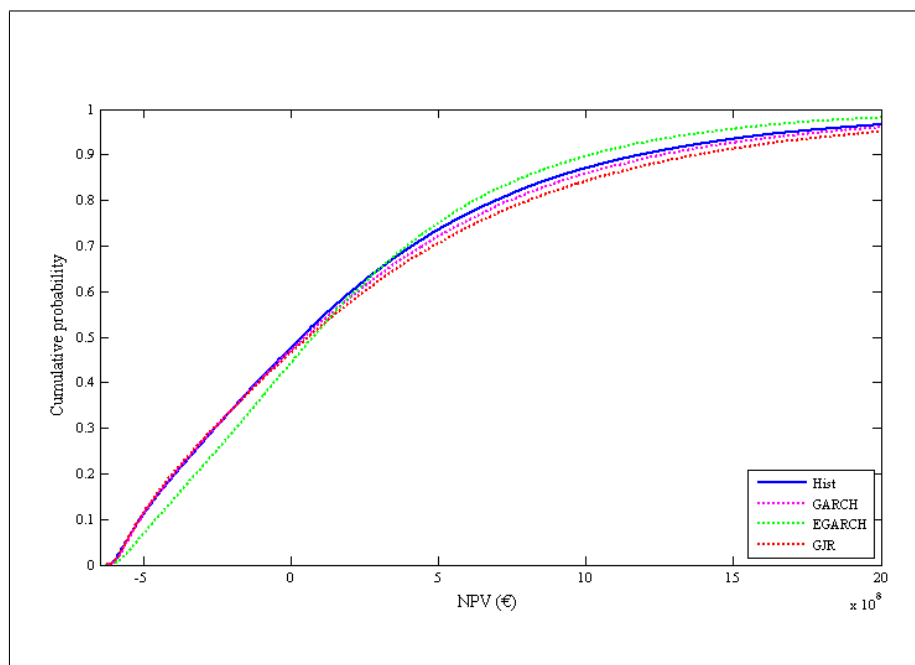**Source: Own work, based on Weber et al. (2010).**

Figure 5.7
Impact Time Resolution on Default Probability
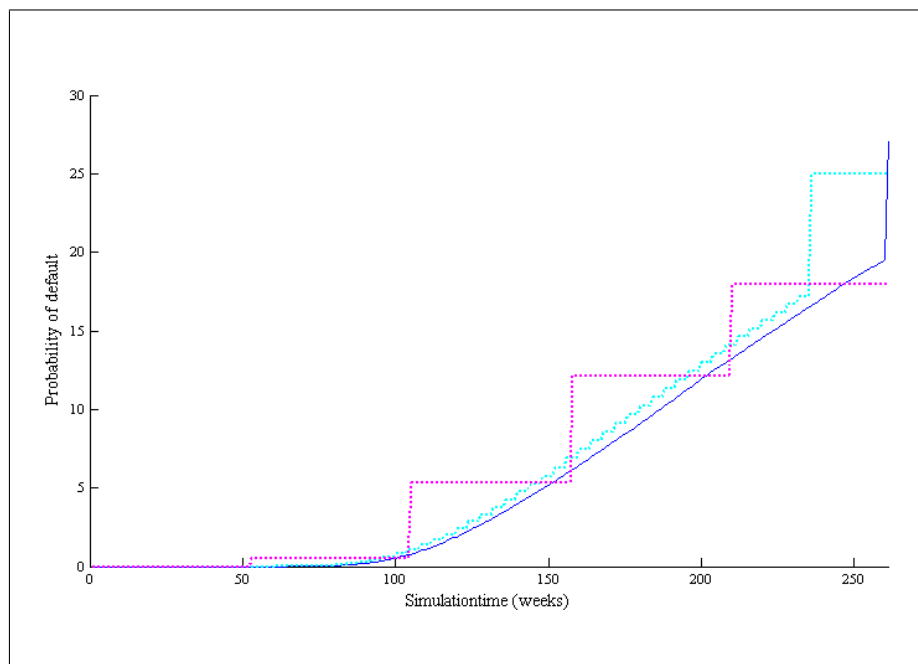
Source: Own work, based on Weber et al. (2010).

Figure 5.8
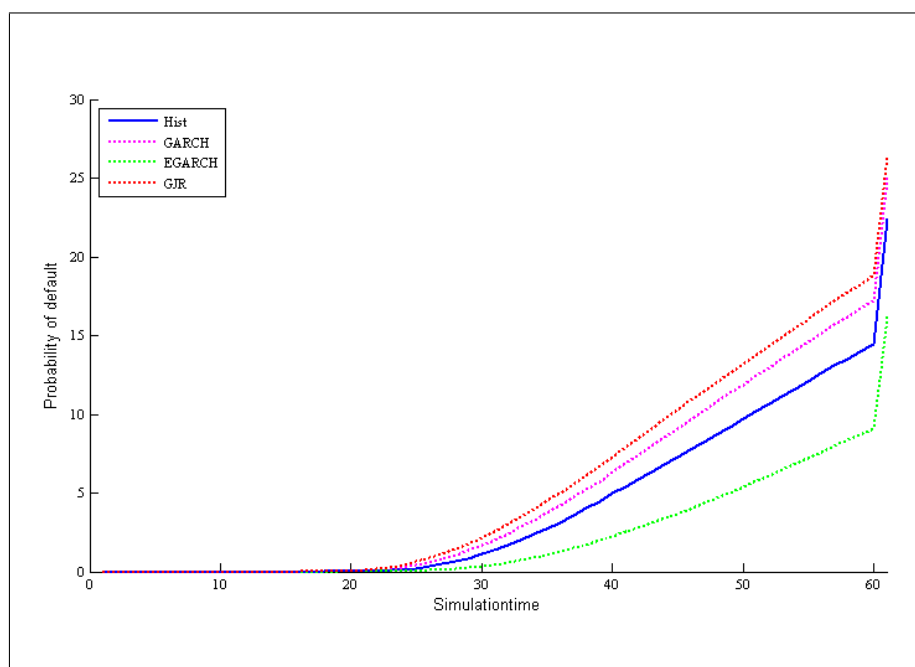Impact Volatility Forecast Model on NPV

Source: Own work, based on Weber et al. (2010).

with yearly resolution since a stream of negative cash flows may be followed by more positive cash flows which compensate for the prior losses. However, on a weekly resolution the project would have defaulted with no possibility of recovering. The explanation of the higher frequency of large NPV estimates is more complicated. One aspect that has to be taken into consideration is the effect of discounting, since higher time resolution leads to smaller discounting steps. As a result, large positive values in the future are discounted with a lower average discounting rate for high-time frequencies, leading to higher NPV estimates today.

5.3.2   Impact of Forecast Complexity

The first issue to be addressed within the area of forecast complexity is how future volatilities are predicted. The PFVT is able to either apply historical volatility values as forecasts for future volatility or to compute those estimates based on different GARCH type models. In addition to the GARCH(1,1) model, I also apply the more advanced E-GARCH and GJR-model. An issue worth mentioning is that forecasts based on GARCH models converge to forecasts based on historical values after a certain period of time. The impact of volatility forecasts on the simulation results is presented in figure 5.8.

Figure 5.9
Impact Volatility Forecast Model on Default Probability

Source: Own work, based on Weber et al. (2010).

As can be seen, the results depend heavily on the applied volatility forecast model. The E-GARCH model leads to a much narrower NPV distribution compared to the other models. The broadest NPV distribution is obtained with the GJR-GARCH model. When analyzing the project's ECDP, reported in figure 5.9, the same effects can be found.

Especially the E-GARCH model is noticeable since it leads to a much lower default probability. The gap between the default probability calculated by the E-GARCH and the GJR-GARCH model is about 10% over the whole runtime of the project. Evaluating which model is best is not possible since the "real" cumulative default probability is unknown. However, my results suggest that the choice of the volatility forecast model is extremely crucial for the simulation results. Hence, it is important to figure out which volatility forecast model is best suited for each factor when valuing a project in practice. The substantial impact of this choice can be seen from the prior two figures. Recent academic works by Bowden & Payne (2008) and Chan & Gray (2006) propose that E-GARCH is the best volatility model for electricity prices. Hence, it could be argued that its application should be favored over alternative models.

In a further step, I investigate the influence of the correlation forecast model. The

Figure 5.10
Impact Correlation Forecast Model on NPV
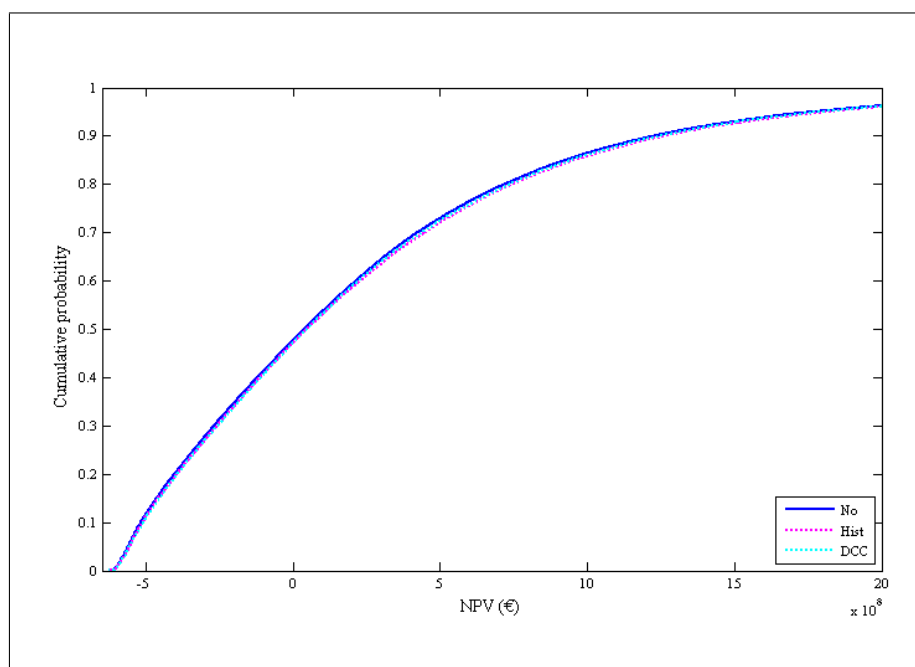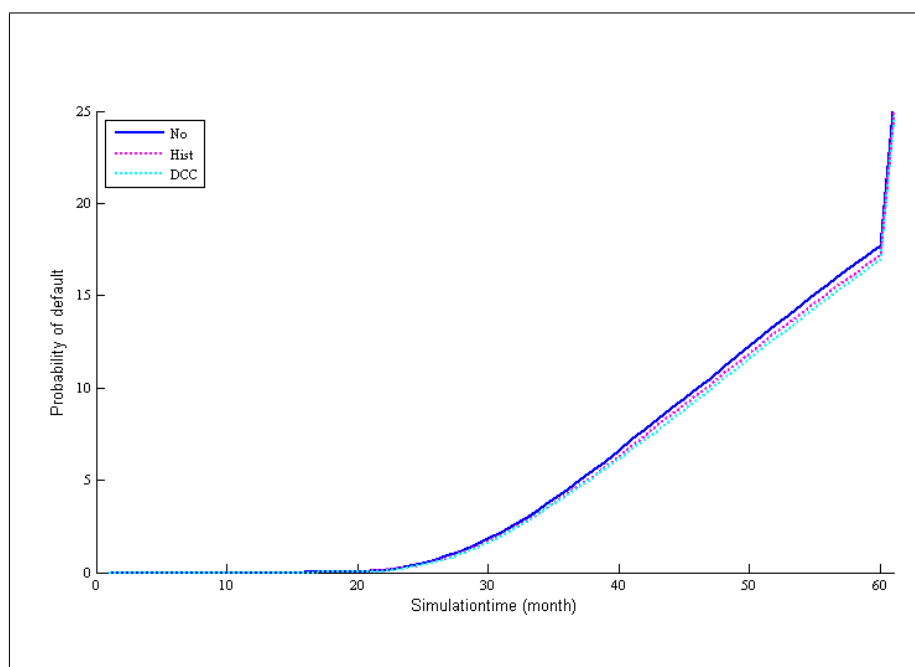

Source: Own work, based on Weber et al. (2010).

PFVT can compute future correlations in three different ways: (i) it assumes that the correlation between all factors is zero in the future, (ii) historical correlations are used as forecasts for future correlations, and (iii) estimates from a DCC model are applied as predictors for correlations. The first method, which assumes zero correlations, has to be interpreted with caution since fundamental economic relationships may be neglected. For example, if a project is simulated whose cash flow depends on gas and oil prices, the assumption of no correlation is clearly misleading since gas and oil prices are highly correlated based on their linking mechanism. However, I integrated this possibility to investigate whether the assumption of no correlation has a significant impact on the results of the case study.[10] Figure 5.10 presents the cumulative NPV distribution function for these three different correlation forecasts.

As can be seen, the choice of the correlation forecast has a limited impact on the simulation results, especially when compared to the choice of the volatility model. The simulated NPV distributions are relatively similar for all three correlation forecast methods. The same is true for the ECDP, which is reported in figure 5.11.

To summarize, my results suggest that correlation forecasts based on a DCC model

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[10]As for GARCH based volatility forecasts, correlation forecasts based on the DCC model converge to forecasts based on historical values after a certain time.

Figure 5.11
Impact Correlation Forecast Model on Default Probability

Source: Own work, based on Weber et al. (2010).

do not significantly improve the result compared to the application of historical correlations. Taking into consideration that the DCC model is rather complicated to implement in a valuation model, I suggest using historical correlations which are easier to handle.

5.4 Concluding Remarks and Future Research

The impact of model complexity on the valuation results is quantified in this chapter. I analyze whether model complexity matters for the valuation of project finance investments in this chapter. The valuation is based on stochastic simulation and performed by a newly developed project finance valuation tool which is introduced in the previous chapter. I analyze the effect on the NPV distributions and the estimated default probabilities. For this purpose, I apply the valuation tool on a power plant case study. I distinguish between two dimensions of model complexity: (i) the complexity of the simulation procedure and (ii) the complexity of the forecast models.

The obtained results are as follows: Regarding the simulation parameters, I find that considering the trade-off between result adequacy and computation time, a

number of 100,000 iterations seems to be the optimal choice. Furthermore, the quasi-market valuation method should be used when valuing projects. Otherwise the project's cost of capital is either over- or understated, resulting in biased valuation results. Analyzing the effect of the time resolution, I find that it is significant for the calculation of the default probability. When using the typical text-book assumption that the cash flow is received at the end of a period, the time resolution also has an impact on the NPV distribution. This is due to the discounting of the individual cash flows. When analyzing the effect of the forecast models, I find that the selected volatility forecast model significantly affects the simulation results. The effect of the correlation forecast model seems to be less pronounced.

To summarize, I am able to show in this chapter that model complexity is important in the context of project finance valuation. However, there are model elements that are extremely crucial while others seem to be less important.

Chapter 6

Summary and Conclusion

The goal of this dissertation is the development of a valuation model for project finance in general and for power plant ventures financed via project finance in particular. Three questions that are essential for the development of the valuation model are posed. The first question concerns the specific requirements for a computer-based project finance valuation tool based on stochastic cash flow modeling and focused on power plant ventures. The second question relates to the choice of the electricity price time series for the calibration of the valuation model, i.e. to the specifics of electricity prices and the German electricity wholesale market. The second and last question relates to the impact of model complexity, i.e. the applied forecast models and the precise simulation procedure, on the valuation results. In the following, I discuss the obtained results in this dissertation for all three questions, putting the results into context. In addition, based on the obtained results, implications for practice and for future research are derived.

The first question addresses the development of a computer-based, self-contained valuation tool. To achieve the stated goals a valuation tool is programmed in Matlab, a powerful programming language for numerical applications. The tool is based on stochastic cash flow modeling and uses various advanced forecast models. Forecasts for level values, volatilities, and correlations are computed. The valuation tool is designed to allow the user to choose which input factors are modeled as stochastic. Furthermore, the tool is user-friendly to assure that it can also be used by non-trained users. To increase the sophistication and the accuracy of the valuation process, the modeling of correlation structures and non-analytical distributions for the input factors is also implemented. The implementation of these extensions to standard valuation tools significantly improves the theoretical foundation of the valuation

results. The main valuation results are probability distributions of future cash flows and of the expected NPV. Moreover, the expected cumulative default probability is estimated.

The second question arises from the lack of academic studies on the German electricity market and in particular on the underlying theoretical price formation mechanism. Thus, the choice of the right electricity price time series is not a trivial task as empirical results for other markets imply the existence of risk premia in electricity futures prices, i.e. these prices are not unbiased estimates of the expected spot prices. To fill in this literature gap, I perform an analysis of the German electricity wholesale market which is located at the EEX. Thereby, I apply the ex post approach. The research question is whether empirical evidence for the the risk premia approach, which is seen in the theoretical literature as the appropriate price formation mechanism, is present. I find significant but also mixed evidence for the existence of risk premia. First, I conduct an analysis of the spot market. Due to the non-storability of electricity, spot contracts are basically futures contracts. The data cover three spot market segments, namely the intraday market, the block contract market, and the day-ahead market; data range from August 2002 to June 2010. I find positive risk premia, both in the block contract market and in the day-ahead market. However, the risk premia in the day-ahead market contracts are only significant on non-working days. The risk premia vary in magnitude and in sign throughout the day. I detect a term structure of risk premia during the sub-period in which all three market segments were simultaneously existent and find that prices were higher in market segments with a longer time-to-delivery. When testing for seasonality and a time evolution of the risk premia, I find no significant results. Moreover, I have to reject the hypothesis of a relationship between the risk premia and the spot price variance and skewness. Second, I analyze the futures market, based on data ranging from June 2002 to June 2010. Due to liquidity considerations I focus on month futures, i.e. futures with a delivery period of one month. I find evidence for significant positive risk premia in short-term futures, i.e. futures with a time-to-delivery up to around three months. When testing for a term structure of risk premia, the results are mixed, since there are periods with increasing and decreasing risk premia. Thus, the evidence suggests that the term structure is not stable. The existence of seasonality in the risk premia cannot be tested with significant results; however, I find evidence for higher risk premia in the winter months. When testing for factors influencing the risk premia a relationship between the risk premia and the variance and skewness of the spot prices has to be denied.

To answer the third question a case study is performed. The case study serves for quantifying the impact of model complexity on the valuation results. I valuate a

power plant and analyze the impact on the NPV distribution and on the expected default probability for certain parameter variations. Model complexity is analyzed along two dimensions: simulation complexity and forecast complexity. I aim to identify model elements which are crucial for the valuation of project finance in practice and thus vary several model aspects in order to analyze their impact on the valuation results. For forecast complexity, I apply different volatility and correlation forecast models, e.g. correlation forecasts based on both historical values and on a DCC model. Regarding simulation complexity, the number of Monte Carlo iterations, the equity valuation method, and the time resolution are varied. I find that the applied volatility forecast models have a strong influence on the expected NPV distribution and on the probability of default. In contrast, correlation forecast models play a minor role. Time resolution and equity valuation are both crucial when specifying a valuation model for project finance. Regarding the number of Monte Carlo iterations, I demonstrate that 100,000 iterations are sufficient to obtain reliable results. Thus, a realistic valuation task must focus on the appropriate forecast of the volatility and the specification of the stochastic modeling.

Several implications for practice can be derived from the obtained results. First, the newly developed valuation tool allows for the deriving of recommendations for the development of other, more general valuation tools. As I identify various crucial aspects of the valuation task, the focus within the development of a valuation tool should be on these aspects. Moreover, in order to increase the computational performance of the valuation task, the obtained results provide decision support for the appropriate balance between model complexity and simplifying assumptions. Second, the obtained valuation results for the power plant venture have the potential to serve as reference values for future valuation tasks. In particular the possibility to estimate the ex ante default probability of the project, an advantage of the chosen modeling approach based on Monte Carlo simulation, provides additional insight compared to other modeling approaches. Third, the results on the price formation mechanism in the German electricity wholesale market, i.e. the existence of risk premia, imply that the futures prices are not unbiased estimates of the expected spot prices. This has several implications for market participants regarding their hedging strategies, the adjusting of investments plans to the expected prices, and the trading in certain market segments. For instance, electricity consumers, i.e. markets participants interested in holding a long position until the maturity of a future, should, based on the results, take their position as early as possible in order to avoid paying a risk premium. An electricity producer, on the other hand, should wait as long as possible before selling its generated electricity. Regarding the choice of appropriate market segments, market participants can use the obtained results to optimize their trading strategies, such as trading in the intraday market, in particular on non-working days.

Based on the obtained results, future research on both the valuation of project finance and the price formation in the German electricity wholesale market also seems promising.

The main avenue for future research on the valuation tool is examining whether the obtained results hold true in a non-energy project finance context. Project finance investments in other industries, e.g. telecommunication or infrastructure, could be used to test the robustness of the results on model complexity. However, it is difficult to obtain reliable data for those industries since little information is publicly available. Furthermore, there are promising extensions that could be included in the developed valuation tool, e.g. more sophisticated valuation methods as the real options analysis and more advanced and realistic forecast models.

Regarding the price formation mechanism in the German electricity market, the obtained results imply that future research in at least two directions seems to be promising. First, further analysis on the time evolution of the risk premia is necessary. Taking the point of view of an efficient market the magnitudes of the estimated risk premia seem to be too high to be explained only with consideration of risk aversion. Thus, parts of the academic literature conclude that the electricity markets are not fully integrated with the broader financial markets. Other parts of the literature conclude that the markets are still relatively young and an explanation based on market fundamentals only is not sufficient. Further research is necessary, in particular on the question whether the risk premia decrease in magnitude with increasing maturity of the market or rather an increasing level of market liquidity. The effect of the entrance of industry outsiders, i.e. speculators, into the market is of interest. Second, an identification of the fundamental drivers of the risk premia seems to be promising. The role of fuels and of emission allowances are of particular interest as recent academic results suggest a relationship between these measures and the magnitude of the risk premia for other markets. However, it is always difficult to generalize empirical results obtained for other electricity market, as every market has its own characteristics which are determined by the underlying generation technology mix.

Having provided answers to several fundamental questions and with promising avenues for future research, this dissertation represents a first step towards a deeper understanding of the largest European electricity market, as well as of the valuation of project finance investments. It aims to position the newly developed valuation tool as a potential instrument for capital providers in their effort to accurately forecast the cash flows and the corresponding value of these capital intensive investments, which will shape the global infrastructure landscape for years to come.
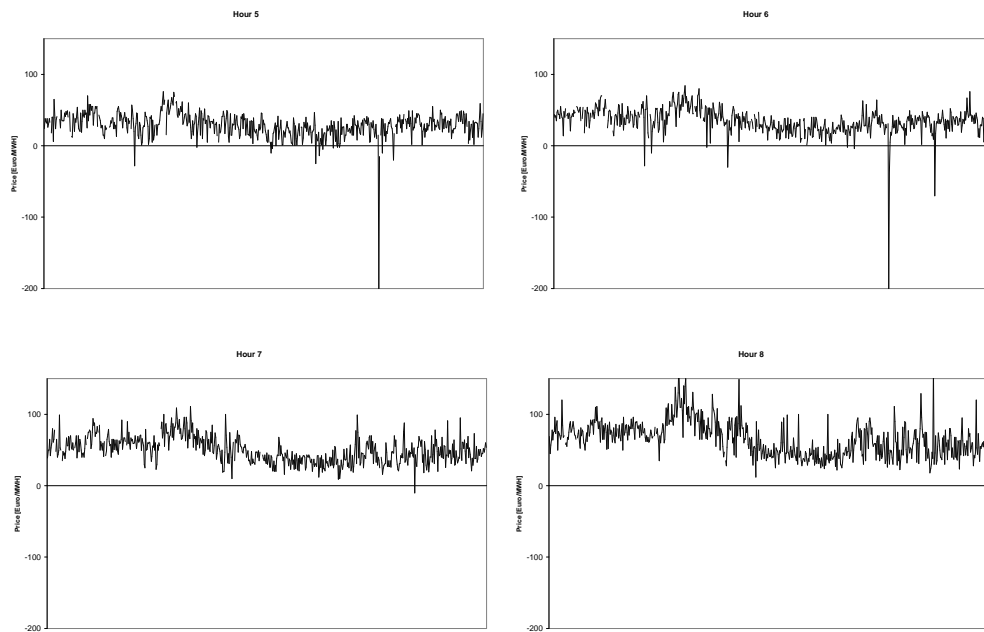
Appendix A

Hourly Prices Intraday Market

The following six figures contain the time series of the 24 hour contracts in the intraday market on working days in the period January 2, 2008 to June 30, 2010.
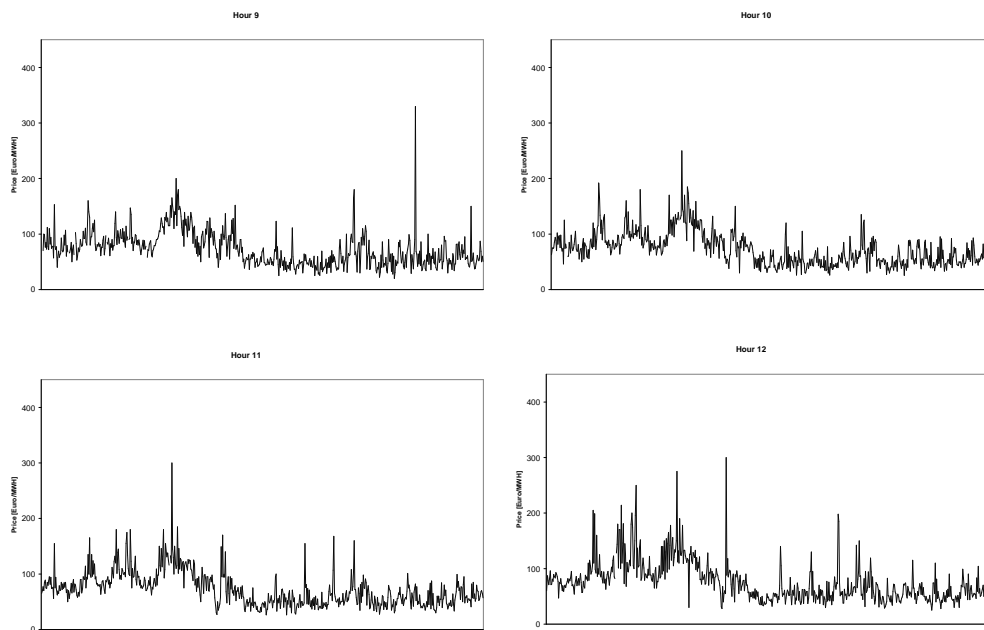
Figure A.1
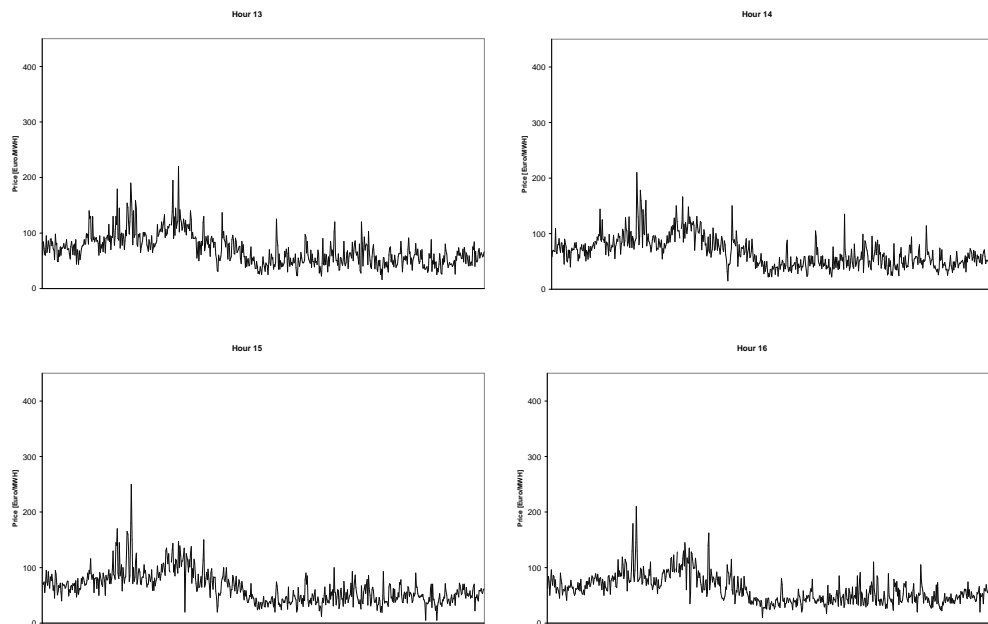Time Series Intraday Market, Hour Contract 1 - 4
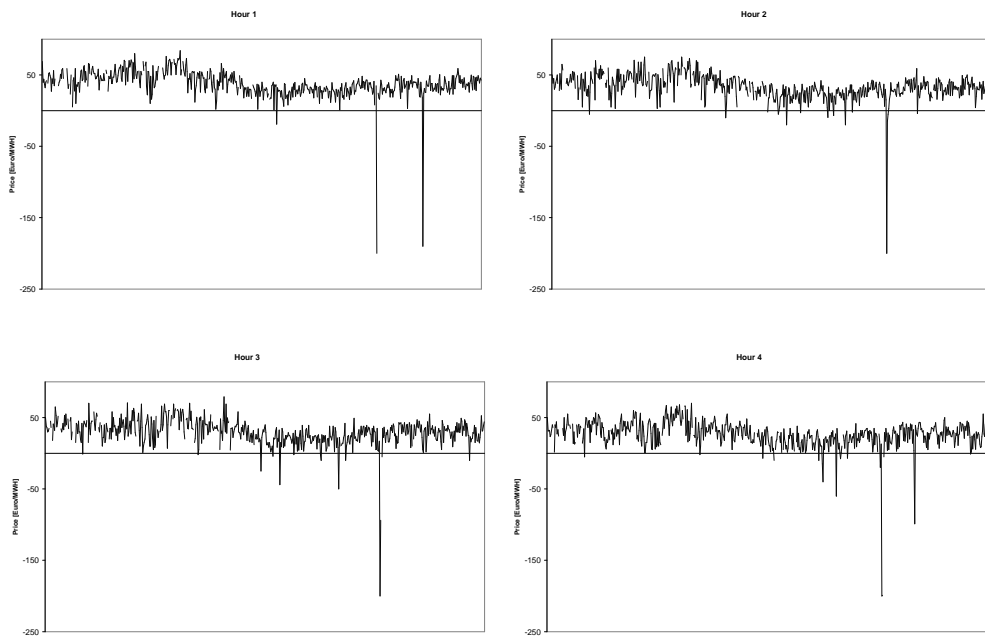
Figure A.2
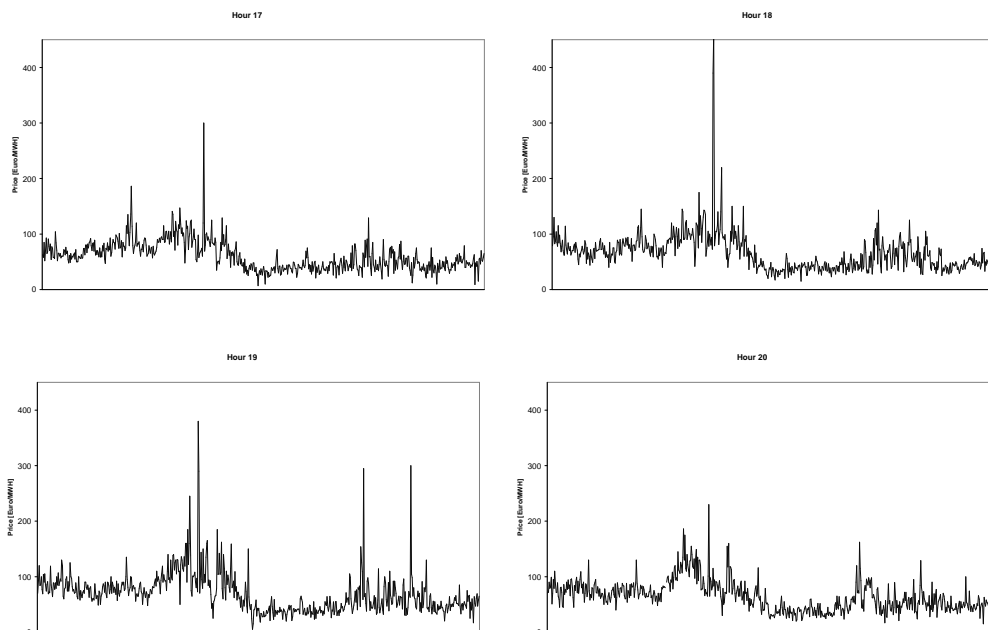Time Series Intraday Market, Hour Contract 5 - 8

Figure A.3
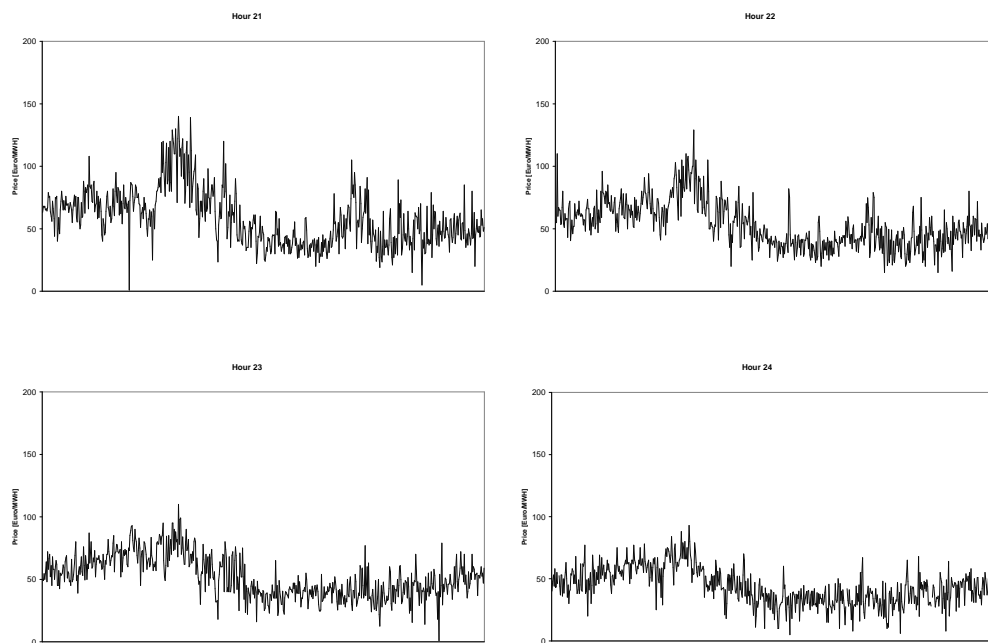Time Series Intraday Market, Hour Contract 9 - 12

Figure A.4
Time Series Intraday Market, Hour Contract 13 - 16

Figure A.5
Time Series Intraday Market, Hour Contract 17 - 20

Figure A.6
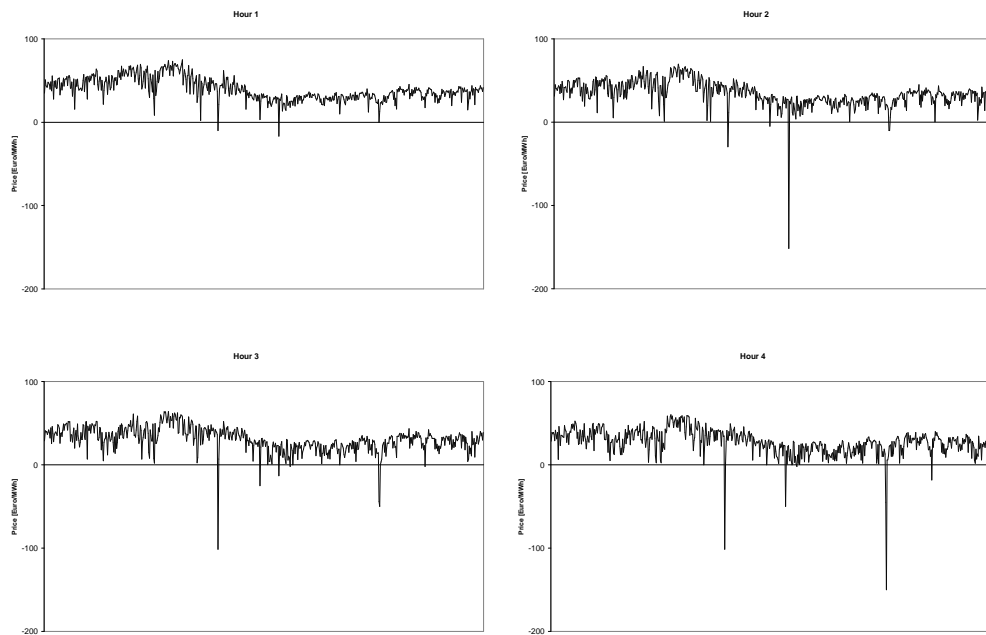Time Series Intraday Market, Hour Contract 21 - 24
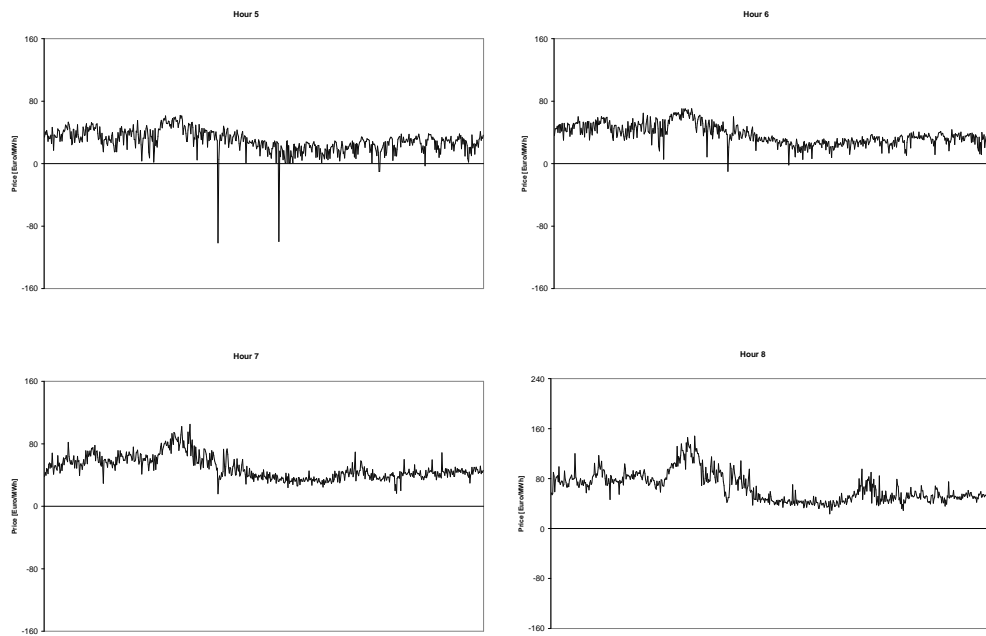

Source: Own work.

Appendix B

Hourly Prices Day-Ahead Market

The following six figures contain the time series of the 24 hour contracts in the day-ahead market on working days in the period January 2, 2008 to June 30, 2010.
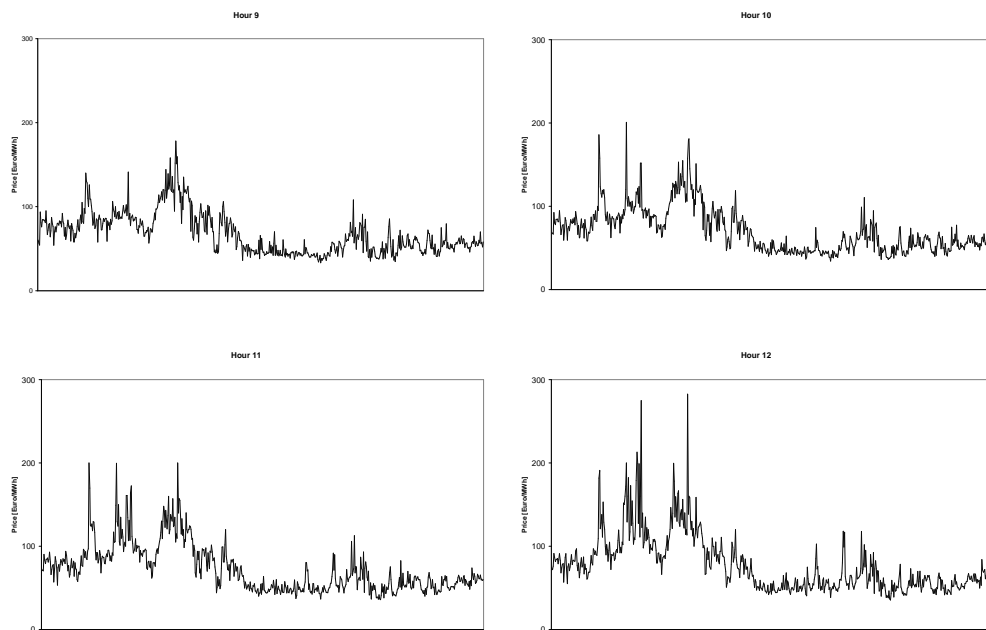
Figure B.1
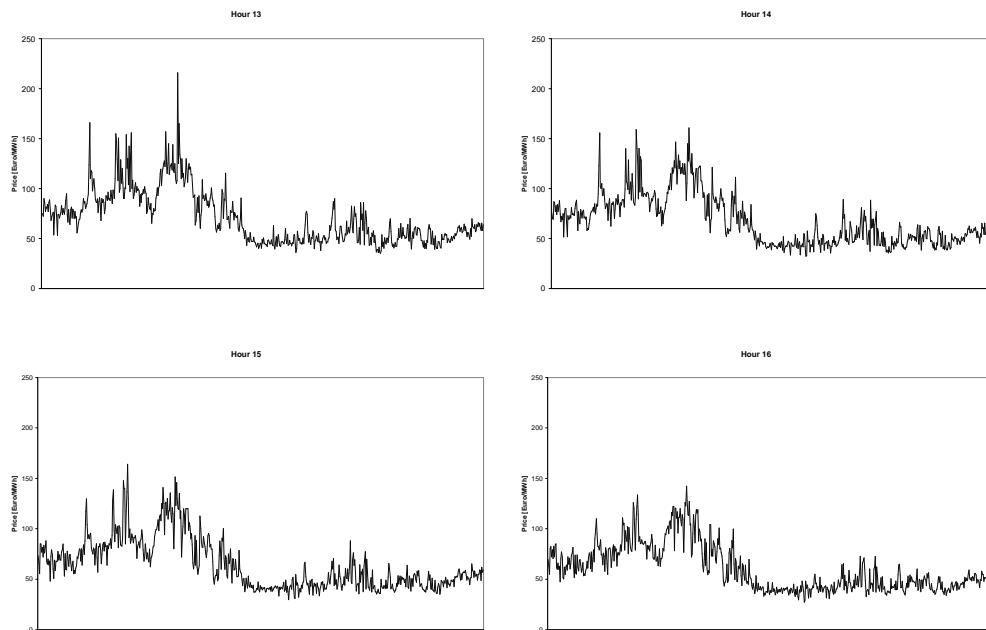Time Series Intraday Market, Hour Contract 1 - 4

Figure B.2
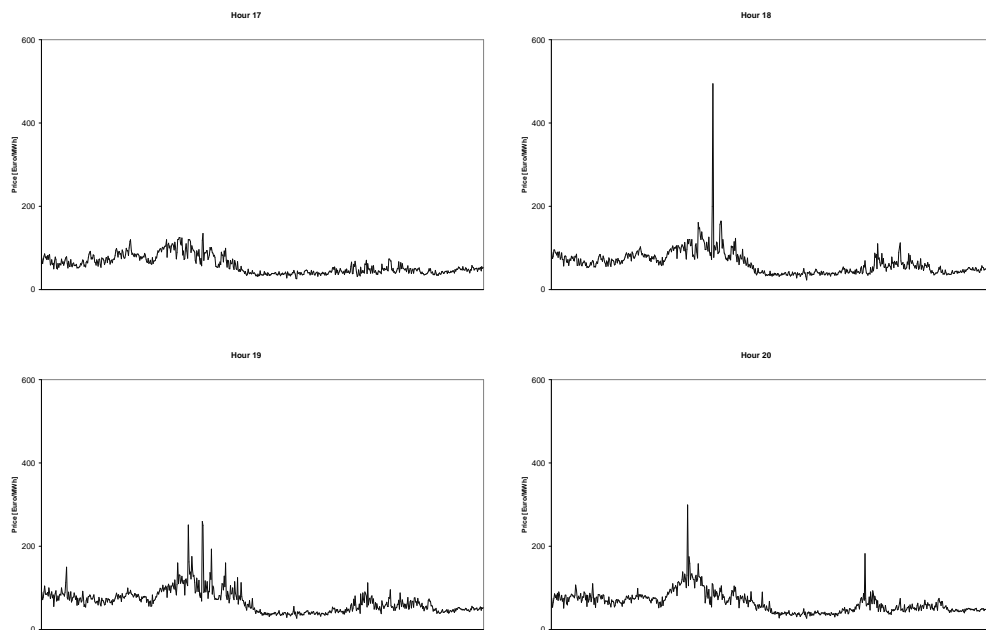Time Series Intraday Market, Hour Contract 5 - 8

Figure B.3
Time Series Intraday Market, Hour Contract 9 - 12

Figure B.4
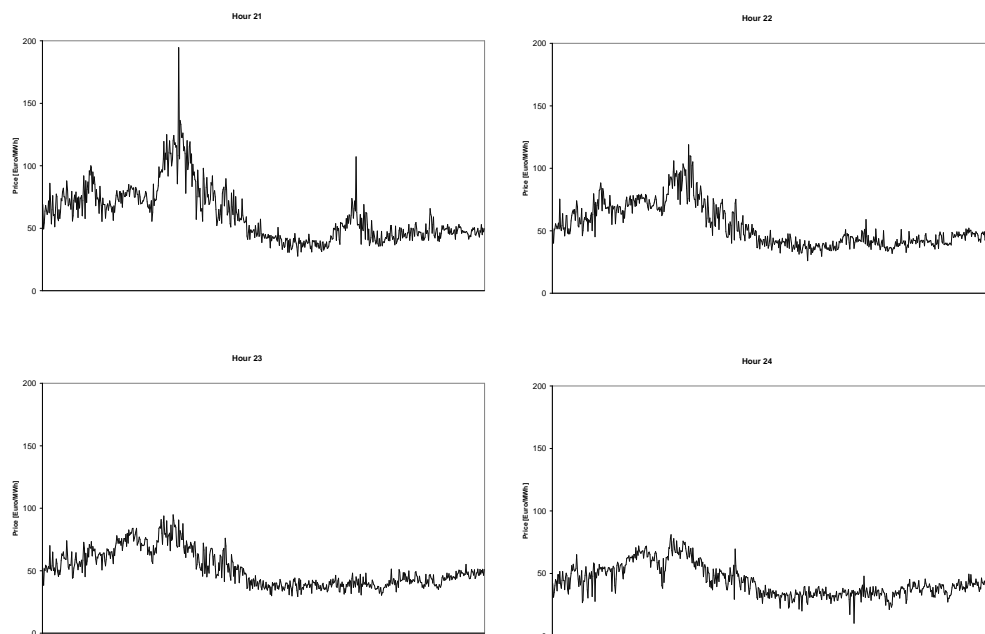Time Series Intraday Market, Hour Contract 13 - 16

Figure B.5
Time Series Intraday Market, Hour Contract 17 - 20

Figure B.6
Time Series Intraday Market, Hour Contract 21 - 24

Source: Own work.

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