CHRISTIAN HUURMAN

Dealing with Electricity Prices

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Omgaan met electriciteitsprijzen

Proefschrift

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Christian Imam Huurman
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Promotor:
Prof.dr. C.G. Koedijk

Overige leden:
Prof.dr. D.W. Bunn
Prof.dr.ir. E. van Heck
Dr. R. Mahieu

Copromotor:
Dr. R. Huisman

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Preface

Dealing with Electricity Prices is the result of my four years affiliation at the Financial Management department of RSM Erasmus University, and the Erasmus Research Institute of Management.

First of all, I would like to thank Ronald Huisman. He introduced me into the world of energy, shared research ideas with me, and guided me through the PhD trajectory in an unconventional and inspirational way. I would also like to thank Kees Koedijk for his support. Furthermore I would like to thank Derek Bunn and Ronald Mahieu for their insightful comments on our joint research projects.

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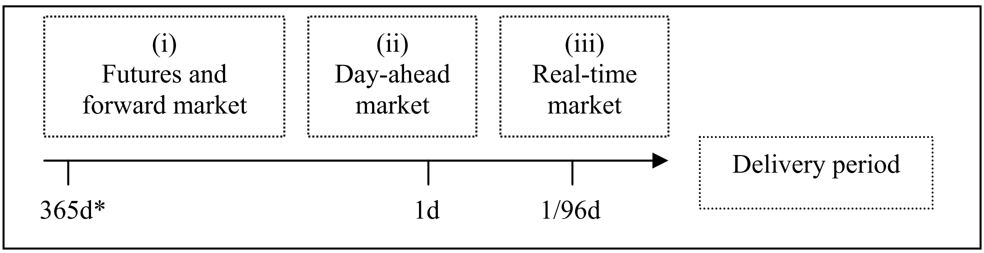
Chapter 1: Introduction

1.1 Background and motivation

Electricity as a flow commodity is unique. Together with oil and gas, it is the most commonly used energy source that our society depends on. A distinctive feature that makes electricity different from oil and gas is that electricity cannot be stored. Given the absence of storage capacity in electricity markets, inventories cannot function as a buffer between supply and demand mismatches. As a result, it is crucial that there is a perfect balance between the amount of electricity that is generated by the power producers and injected on the network for transmission (supply-side), and the amount of power drained from the grid by distributors, who sell the power to the end-users (demand-side). Usually a single national transmission system operator ensures the integrity of the power system in a country (e.g. activities can include monitoring security of supply, maintenance and providing balancing services). These parties need to accurately forecast demand and/or supply to secure the equilibrium. Electricity is a vital commodity for the economy we live in. Millions of industrial and residential end-users depend on it (e.g. power consumption for office IT systems or microwave) at every precise moment of the day. As a result, demand is a rather inelastic function of price. All these imply that electricity delivered at different moments (hours, days, week, months and seasons) is perceived as a distinct commodity. More than a decade ago, this distinct feature would not matter for the determination of power prices. Back then, the worldwide electricity sector was vertically integrated. Regulators fixed prices that reflected generation-, transmission and distribution costs, and these power prices changed seldom.

The 1990s has seen the start of the worldwide deregulation process in the electricity industry. Since then, electricity prices were soon to be based on the market rules of supply and demand. New players entered the industry, and exchanges were introduced where participants could trade in contracts that met their needs. The energy world that traditionally consisted of a few producers and a dozen of distributors, would never be the same. In order to exploit the wider range of choices, lowest prices and the best services provided by the suppliers, end-users now have to act. They have to make purchase decisions in line with their cost and risk preferences. Surveys on the Dutch and UK market indicate that (in particular private) end-users have difficulties with doing that: they switch rarely from supplier. And when they do, the chance that they end up with a more expensive one is roughly the same as choosing a cheaper one (Van Damme, 2005). As a result of the liberalization trajectory, risk has been transferred from the supply side to the end-user. Electricity prices are characterized by a unique feature that cannot be observed in any other market: extreme price movements that occur frequently and stem from the aforementioned non-storability of electricity. A comparison of daily volatility figures (measured as standard deviation of returns) between the electricity market and 'traditional' commodity- and financial markets gives a first impression of the volatile market conditions that electricity market participants face: T-bills less than 0.5%. Stock indices 1% -1.5%. Commodities like oil and gas 1.5%-4%. Volatile stocks >4%. Electricity >50%. (Weron, 2004). This has triggered the demand among electricity market participants for derivative contracts, as futures and alike, in order to insulate themselves from electricity spot price risk. With price risk, the uncertainty is meant that is embedded in the price process of electricity. Similar to other commodities, contracts designed to trade electricity along for immediately delivery, or on a pre-specified future moment and price[1], are respectively referred to as spot-, and derivative contracts. Because the electricity spot price path is non-standard (i.e. price spikes, time-varying volatility, seasonality and regional behavior) from the spot price processes observed in traditional markets, the value of an electricity future cannot be easily replicated in terms of the underlying spot price path. Although academic research on valuation of derivatives[2] is well-established, little is known about the valuation of electricity derivative contracts (Bessembinder and Lemmon, 2002). This is due to the fact that electricity is non-storable. As storability is a crucial assumption in most derivative valuation models (i.e. Black-Scholes option theory[3]), these methodologies cannot be meaningfully applied. It is therefore of the utmost importance to gain understanding about alternative methodologies in order to suggest additions to traditional pricing and portfolio models.

There are three generic types of electricity markets: (i) futures and forwards markets, (ii) day-ahead markets and (iii) real-time markets. Figure 1.1 depicts the symbiotic relationship of these markets.



NB: d = days before delivery (expiration of contract).
*Contracts are also traded with a maturity horizon > 365 days.

Textbox 1.1: Planning horizon and symbiotic relationship between the market places

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1 While traditional assets such as stocks and bonds can be only settled financially, commodity derivatives can be settled both financially and physically. Here financially means that the contract secures the exchange of cash flows rather than the physical underlying instrument itself, in a pre-specified point in time (generally at maturity).

2 In the 18^{th} century the first derivative, back then referred to as ‘to-arrive’ contract but nowadays known as a future contract, was traded by grain farmers who wanted to sell their crops against a fixed price ahead. In this way, he ensures cash flows that otherwise would be subject to the variation of the harvest price on spot, and can finance the production process.
After the successful launch of a trading place, where market participants could exchange standardized contracts, commodity derivative markets flourished ever since. The exchange standardizes contracts in term of quantity, quality, maturity as well as the trade-, settlement-, and delivery procedures.

3 Here it is assumed that the underlying spot instrument can be continuously traded. This makes it possible to continuously replicate the derivative out of a combination of the underlying spot contracts. Hence, it implies that the option value can be derived from this replicating portfolio, which should be updated continuously to keep it risk neutral. Because electricity cannot be stored, the replicating portfolio lasts only for a very short moment in time (Geman, 2005).

(i) Futures and forward markets
In 1993, the Nordic Power Exchange was the first exchange to trade electricity futures. It was not until 1996 that a U.S based exchange, the New York Merchantile Exchange started offering power derivative products. In 2004, four of the six most active electricity derivative exchanges worldwide are located in Europe: the Nordic Power Exchange (NPX), European Energy Exchange (EEX), Amsterdam Power Exchange (APX)[4] and the Paris Power Exchange (PPX)[5]. Soon after the introduction of electricity futures its popularity decreased steadily among investors. Currently the Over-The-Counter (OTC) forward contracts are by far the most actively traded derivative contracts offered on the electricity exchanges, followed by futures and options (Eydeland, 2003). Unlike electricity future contracts, electricity forward contracts are not standardized by the exchange but by an intermediate party, and therefore can be structured to the needs of the contract parties (e.g. delivery in certain hours or days, or at a certain geographical location). Another difference is that forward contracts do not require margin deposits for order placement and daily marked-to-market payments, which also enables individuals or firms who have limited access to daily cash to become a contract party. The high operational and financial flexibility explains why OTC contracts have soon become the main cash cow of electricity derivatives exchanges worldwide.
A point worth emphasizing is that forward prices and future prices are very close to each other in practice, despite above-mentioned differences. This is because the price variation in the underlying asset is the most important explanatory variable (Geman, 2005). We therefore make no distinction in this research between the two contract types when we model their price behavior (See Chapter 5). We therefore will use both terms in this Thesis interchangeably.

(ii) Day-ahead markets
Most exchanges organize both a derivative market and a spot market. This ‘spot’ market is actually a day-ahead market. Here agents submit their 24 hours bidding scheme to the exchange for physical delivery for one, more or each hour on the following day. After market closure time the exchange quotes separate market prices for each specific hour in the next day. Hence, in electricity markets the delivery does not take place on ‘spot’ (meaning immediately after the transaction), but in a minimum time span given the technical constraints between trade and delivery. This is a typical one-day horizon, since the independent system operator needs this time-span to guard the integrity of the power system (Geman, 2005).

There is a close relationship between the derivative market and spot market, and most exchanges have both trading platforms. For instance, on the EEX (based in Frankfurt) a range of futures with different delivery periods (month(s)-ahead, quarter(s)-ahead and so forth) are traded, all with the daily day-ahead price index as underlying instrument.

[4] In 2002, the European Energy Derivative Exchange (ENDEX) acquired the derivative activities from the APX. Since then, the APX focuses on day-ahead contract trading only.
[5] Geman (2005)

	Year of establishment	Capacity (Giga Watt)	Conventional thermal	Nuclear	Hydro & other
APX (Netherlands)	1999	21	95%	4%	1%
EEX (Germany)	2000	127	62%	31%	7%
NPX (Scandinavia)	1993	91	28%	24%	48%
PPX (France)	2001	116	30%	51%	19%

Conventional thermal fuelled capacity: oil, gas, coal and lignite.
Hydro fuelled capacity: reservoir and river. Other fuelled capacity: wind and solar.

Table 1.1: Capacity figures of EU countries with most active wholesale power markets
Source: Speck and Mulder (2003)

These futures all settle financially (which means in cash) on a monthly basis[6]. The exchange offers the participants the possibility to place (hourly) bids on the spot market corresponding with the futures position, to ensure physical settlement for the delivery period under consideration (Geman, 2005). In table 1.1 we have listed some characteristics of the four most liquid markets in Europe: APX, EEX, NPX and PPX.

(iii)Real-time markets
The real-time or balancing markets have the shortest planning horizon of the market places depicted in textbox 1.1. This market is used for balancing short-term deficits and surpluses of electricity on the grid. Typically the transmission system operator is responsible for the balancing activities, which include injecting power into the grid when suppliers are short of electricity. It also includes the disposal of excess power when customers take less power than expected, or generators supply more than expected. The design of the balancing system (i.e. market- or regulative-based system) varies between countries.

There is symbiotic relationship between the market places (i, ii, and iii) displayed in textbox 1.1. The planning horizon of these markets (and the maturity horizons of the contracts) is perfectly complementary, which allows suppliers to meet their delivery obligation in three phases: Long before maturity, let's say a year, a substantial percentage of the expected demand is met by a portfolio of futures- or OTC contracts purchased in (i), In the second phase, let's say a week to a day before maturity, the actual demand can be more accurately forecasted and the supplier readjusts her position accordingly by purchasing OTC contracts and spot contracts on respectively (i) and (ii) that secure the

[6] Essentially, also yearly and quarterly contracts settle on a monthly basis. This is because these contracts are split into contracts with a shorter delivery period just before they mature: i.e. a year-ahead contracts is split into three monthly contracts with exact complementary delivery months for the first quarter, and three quarterly contracts for the remaining part of the year. Then at the end of the first quarter, the quarterly contracts that are about to mature, will be split into three monthly contract as well. This procedure is called cascading. The financial settlement price quoted on the last trading day of the month equals the monthly average Phelix price of that delivery month (Geman, 2005).

delivery of power a week- or day-ahead. The closing phase starts on the supply day itself, and the delivery obligation is fully met via the outstanding load being purchased or sold via (iii). In this way, electricity price risk can be significantly reduced by allocating the risk over the contracts available in the three symbiotic market places.

On today's derivative markets three types of participants are active: (1) Hedgers is the traditional group of participants. They take a derivative position in order to insulate themselves from fluctuations in spot prices. (2) A second group is the speculators, who try to exploit their ability to forecast spot price movements. They take a derivate position accordingly, and hope to generate income from it. (3) Arbitrageurs are the third class of participants who exploit mispricing in the markets. Their strategy entails simultaneously entering positions in two or more markets, and hereby locking in a risk-free profit. In derivative pricing theory, fair prices of derivative instruments are based on the assumption of no-arbitrage opportunities. Due to the non-storability of electricity, the no-arbitrage condition cannot be meaningfully implied; electricity forward- or future traders cannot make their portfolio risk neutral by trading these derivatives on one side while maintaining a position in the underlying commodity for the time until delivery on the other side. Note that certain types of arbitrage strategies can be implemented in electricity.[7]
Observe that each group of market participants has its own unique function in the market system. In particular, (1) brings risk to the market, (2) brings cash and expectations, and (3) brings price efficiency.

1.2 Research objectives

The overall aim of this thesis is to address important empirical and methodological issues that are central to price modeling and portfolio management across the spectrum of electricity markets (textbox 1.1.). Due to the short existence of wholesale spot and derivative power markets, the number of empirical studies that examine these issues are still relatively small. We contribute to the existing literature by providing empirical tests for untested hypotheses, propose alternative methodologies for price modeling and show how traditional portfolio theory can be applied to electricity markets with the proper modifications. The research consists of empirical studies using time-series analysis, extreme value theory and panel data methodology in order to suggest additions to traditional price models for spot- and derivative contracts, and portfolio theory.

1.2.1 Electricity spot price modeling

Day-ahead and real-time markets play a key role in the performance of a balancing system in today's deregulated markets, but only a very few studies have examined the price relationship on these two markets. Chapter 2 studies the historical development of imbalance prices, volumes and the spread between imbalance prices and day-ahead prices, to disclose changes that are consistent with the increase of allocative efficiency imposed by the liberalization. In Chapter 3 we focus on a method to capture the price spikes observed in day-ahead electricity markets through the selection of a distribution function. We propose the Student-t distribution as an alternative to the normal distribution as it is

[7] E.g. time-arbitrage strategies; involve taking simultaneous positions in electricity spot contracts that secure electricity delivery in baseload hours (all hours of the day) and peakload hours (certain hours of the day).

capable of incorporating fat-tailed behavior of a distribution (here the tails reflect the the occurrence of price spikes) through its number of degrees of freedom. Prior research fails to provide a satisfactory empirical framework to describe the dynamics on an hourly (intra-day) basis. Chapter 4 therefore concentrates on a modeling framework that exactly matches the market microstructure of day-ahead markets. It advances a unique panel data framework to modeling the dynamics of hourly day-ahead prices, being hourly-varying mean price levels and hourly-varying mean reversion.

1.2.2 Electricity derivative price modeling

Any forward-, or future price can be decomposed out a spot price forecast component and a risk premium component. Fama (1984) proposed a model for joint measurement of these components embedded in derivative prices. Following Fama (1984) we concentrate on the existence of these components in electricity derivative prices. In Chapter 5, we attempt to disclose how these components embedded in electricity forward- and future prices change over the different contract maturities.

1.2.3 Electricity portfolio management

As discussed in the previous section, the deregulation has led to a risk transfer within the industry chain. In today's electricity markets, end-users can switch from one supplier to the other. Hence, they have to decide what portfolio strategy goes in line with their cost-risk preference. In Chapter 6 we consider an end-user who wants to allocate her risk over a combination of market contracts with different maturity horizons. We test whether the concept of mean-variance portfolio theory, with some proper modifications, can help the end-user to derive the optimal portfolio strategy.

1.3 Structure of thesis

Figure 1.2 illustrates the linkages between the Chapters. The remaining part of this thesis is structured into Chapters according to the above-discussed research issues.

Chapter 2, 3 and 4:
Spot price modeling

Chapter 5:
Futures & forward price modeling

Chapter 6
Electricity portfolio management

Chapter 7:
Conclusions

Textbox 1.2: Outline research and symbiotic relationship between Chapters

Chapter 2: More efficiency through liberalization[8]

-Empirical study on Dutch real-time market-

2.1 Introduction

As of 1 July 2004, the Dutch power market has been liberalized. Households and companies can now choose their own electricity supplier. The liberalization is part of EU policy to create an internal competitive market. The design of these reforms started a decade ago and is documented in the 96/92 EC Directive.[9] The aim is to increase the efficiency in the power supply chain, while safeguarding security of supply. To accomplish this, it necessitates various reforms, such as allocative changes in property rights for national regulatory authorities, network and transmission operators, the power producers, wholesalers, consumers and other market participants in each EU member state.

The continuing academic debate in privatisation theory regarding industries that are of vital importance for the social welfare and involve public goods, such as the gas and electricity sector, centers around the proper level of government regulation and the level of efficiency gains that can be achieved by the choice of governance structure. Megginson and Netter (2001) provide empirical evidence that privatized firms are on average 2% percent more efficient than state-owned firms. According to them, the efficiency increase can be addressed to the use of less employees, reduced dependency on government subsidies, lower production costs and less financial debt on the firm's balance sheet. It is expected that liberalization of the energy market will lead to lower electricity prices. Hall (2001) notes that in early liberalizing EU countries, such as the United Kingdom, Finland Norway and Sweden, the end-users in the business sector predominantly benefited from these price reductions.

In this Chapter, we examine to what extent the recent liberalization has led to a change in efficiency on the Dutch power market. We do this by examining the historical development of electricity prices on the day-ahead market and electricity prices and electricity volumes on the real-time market, often referred to as the balancing market. While the day-ahead market secures delivery of electricity on hours in the next day, the balancing market is used for balancing short-term deficits and surpluses of electricity on the grid over a 15 minutes horizon[10]. Until now, only a few studies have concentrated on the historical development of prices on day-ahead and real-time markets. Longstaff and Wang (2004) concentrate on the price difference observed between these markets in the U.S. (in particular, the PJM[11] market), and attribute it to consumption-based risk factors. Boogert and Dupont (2005) study the opportunity to exploit the price difference observed between the Dutch day-ahead and real-time market, and conclude that there are no

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[8] Part of this chapter is based on: R. Huisman and C. Huurman (2004), "Meer efficiëntie door liberalisering electriciteitsmarkt" *Economisch Statistische Berichten*, 89 (4445), pp. 510 – 512. We thank participants of European Electricity Markets conference in Lodz (20-22 September 2004) for valuable comments.

[9] The 03/54 EC Directive is currently effective, and is an updated version of the 96/92 EC Directive.

[10] See Chapter 1 for discussion on the symbiotic relationship between these markets .

[11] The PJM (Pennsylvania New Jersey Maryland) market is the world's largest energy exchange in terms of trading volume (capacity: 164 GW). Source: www.pjm.com

profitable trading strategies on the Dutch market. We also study this price development on the Dutch market, but attempt to shed light on the issue whether the liberalization process has led to an efficiency change, and formulate hypotheses to test for that on the Dutch power market. To our best knowledge this has not been done before. A point worth emphasizing is that the design of the balancing market varies from EU member state to member state.[12] The balancing market in the Netherlands is one of the few[13] national markets in the EU where balancing charges are set by the market itself (opposed to a regulative-based mechanism) and there is no single dominant balancing generator. We find evidence of price and volume changes observed on the Dutch power markets that are in accordance with a higher level of allocative efficiency. This result provides at least partial evidence of a successful liberalisation process of the Dutch electricity market.

The Chapter is structured as follows. In section 2.2 we discuss the concept of efficiency in light of social welfare theory and EU- and Dutch policy. Section 2.3 sets out the Dutch balancing market model. It presents the hypotheses to test for changes in balancing prices, and volumes that are consistent with increased efficiency in this market. Section 2.4 presents the empirical results. Section 2.5 concludes this Chapter.

2.2. The concept of efficiency

Below we examine the concept of efficiency, as formulated by EU- and Dutch policy makers (section 2.2.1), and as defined in the existing economic literature (section 2.2.2).

2.2.1 Efficiency: A central objective for policy makers

The 96/92 EC Directive concerning the creation of an internal gas and electricity market in the EU has been effective since December 1996. It functions as the blueprint for the current ongoing market liberalisation trajectory.[14] Note 4 of this Directive reads as:

> "Establishment of the internal market in electricity is particularly important in order to increase efficiency in the production, transmission and distribution of this product, while reinforcing security of supply and the competitiveness of the European economy and respecting environmental protection."

And the policy report published in 2002 by the Dutch Ministry of Economic Affairs states:

> "Efficiency is a central goal in the creation of an internal market…..The freedom of choice for both suppliers and consumers is an important incentive to achieve economic efficiency.

Hence, economic efficiency and supply security are central policy objectives. The Dutch liberalization trajectory is part of the EU policy to create a free internal energy market that should result in the achievement of these objectives.

The European Commission has recognised the need for a framework to monitor the development of this process with respect to the objectives formulated. Therefore the special European committee EG DG TREN has been established to design a sound

[12] The EU member states that implement the 2003/54 EC Directive and have a balancing market are Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Luxembourg, The Netherlands, Portugal, Spain, Sweden, United Kingdom, Norway, Estonia, Latvia, Lithuania, Poland and Slovakia.

[13] Others are the United Kingdom and Spain.

[14] Currently, its successive legal act 2003/54/EC is effective.

monitoring system. They publish annual benchmarking reports. These documents disclose that monitoring is a non-trivial task due to the lack of consistent data and lack of harmonisation between existing data in the Member state countries. Market indicators that are used for monitoring efficiency and supply security include historical prices and volumes observed at the day-ahead and real-time markets, and the level of reserve capacity that is traded on the real-time electricity markets.[15] Van Werven and Scheepers (2004) rank a set of indicators along criteria as validity, availability and reliability and conclude that balancing prices and volumes score overall high as monitoring indicators.

2.2.2 Efficiency: perspectives from economic literature

Welfare economics deals with the efficient use of resources. It attempts to answer the question whether the market allocates resources among their competing users in such a way that maximum welfare is reached. Prior literature from welfare economics offers differing theoretical perspectives on the concept of economic efficiency: (i) allocative efficiency; (ii) x-efficiency. (i) A large volume of research was developed upon the neoclassical theory, which concentrates on deviations from the idyllic picture of an allocative efficient market economy. In these studies potential factors such as the degree of competition (monopoly versus competition) and tariffs are identified to explain resource misallocation. Harberger (1954) states that optimal resource allocation is reached when all firms are operating on their long-term cost curves in such a way that each firm generates an equal return on its invested capital, and markets are cleared. Markets are then efficient when it allocates supply to demand in such a way that the bid of the producer (supply) with the lowest marginal costs structure is matched with the purchase order of the distributor or end-user (demand). (ii) The strand of research on X-efficiency has evolved into a respectable discipline in applied economics. The theoretical back-up of X-efficiency follows the study of Leibenstein (1966). Leibenstein argues that the empirical findings of allocative gains in the neoclassical studies are marginal as compared to the efficiency gains from a difference source that he found in his study, which he name as X-efficiency gains. This type of efficiency is rooted in the internal operation of the firm. For instance, Button and Weyman-Jones (1992) mention that nuclear-based power generators offer more prestige to management than gas-based power plants. This would typically not be recognized as an indicator for efficiency in the neoclassical stream.

Both studies offer very little guidance on how to measure X-efficiency empirically.

Megginson and Netter (2001) provide an excellent review of empirical studies that investigate the potential welfare gains that arise from privatization trajectories that have been initiated by many governments worldwide during the 1980s and early 1990s in various industries (but not the electricity industry). The fraction of empirical literature that studies the potential welfare gains that arise from liberalization trajectories is far less developed.

Wolfram (1999) sheds light on the issue of welfare gains in a deregulated British (spot) power market. She utilizes measures of marginal costs that reflect the market power in the industry to examine the generators' cost-price mark-ups. She finds that the prices charged by generators' are above the marginal costs but not up to the level predicted from theoretical models. This could be explained by strategic behaviour to deter entry of a potential entrant, or regulatory constraints. Her analysis also shows that in an allocative

[15] Policy report Ministery of Economic Affairs (2002), EnergieNed (2003).

efficient market, the cheapest generators produce the most, and the more expensive generators only produce when demand is high.

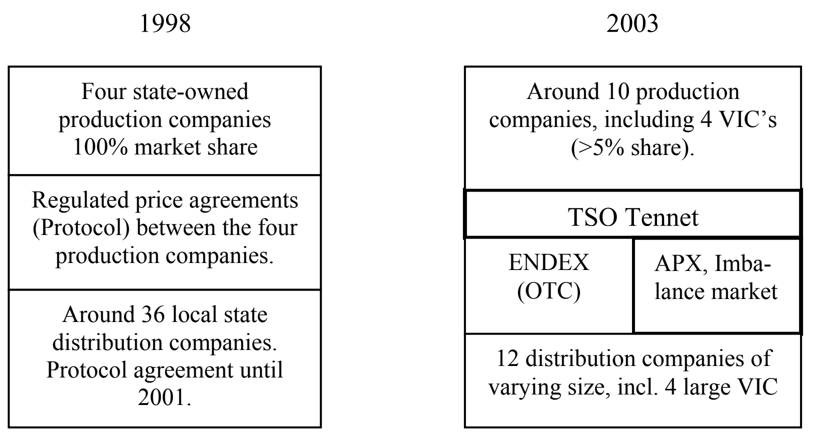
Our definition of allocative efficiency is closest to the definition as given in neoclassical studies and goes in line with the observation of Wolfram (1999) that in efficient power markets the cheapest generators meet most of the demand volume and the more expensive generators only produce when demand is high. In this Chapter we do not aim to measure efficiency changes that stem from the liberalization process in electricity markets. Instead we test hypotheses on changes in balancing price and balancing volume that are in accordance with a higher level of allocative efficiency.

2.3. The Dutch wholesale power markets

Below we discuss the characteristics of the Dutch day-ahead market and balancing market (section 2.2.1) and its price mechanism (section 2.2.2). In the closing subsection, we present the hypotheses that we will test in this study (section 2.3.3).

2.3.1 The day-ahead market and balancing market

From the early 1970s onwards, cooperative agreements constituted the basis for a closed system of supply. Costs were pooled between four state-owned production companies, and reflected the average production, generation and distributional costs. This system lasted for the next 25 years. Under the 1986 OVS agreement, this cost-pooled based system resulted in standard prices that were equally charged to all local distributional companies. When the Dutch government effectuated the 1998 Electricity Act as part of the EU policy, several reforms were soon to follow in the Dutch wholesale market. This can be seen from textbox 2.1. We now discuss the bold-faced textbox 2.1.



Vertical Integrated Companies (VIC): Essent (22.8%), Electrabel (22.8%), Nuon (20.9%), EON (8.6%). (share of national production capacity (19 GW)

Textbox 2.1: Dutch liberalisation reforms from 1998-2003
Source: EnergieNed (2003), Newbery et al. (2003), Speck and Mulder (2003)

In 1998, TenneT was established in 1998 as the national state-owned transmission system operator (TSO). TenneT is responsible for the national high-voltage grid that connects both to the regional and European grids. In particular, TenneT monitors the reliability (e.g. maintenance) and continuity of the electricity supply. A year later the first electronic exchange in continental Europe for trades in day-ahead electricity contracts was established, being the Amsterdam Power Exchange (APX). In 2001, TenneT acquired the APX. Currently the APX accounts for 15% to 20% of the net electricity consumption in The Netherlands.

On the balancing market, TenneT categorizes offered residual capacity into balance-management capacity that is actually used to offset the power deficit and power surplus positions within a PTU, and reserve capacity, which serves as a buffer in case the level of balance-management capacity is insufficient. On this market, program-responsible (PR) companies, who supply power to and consume power from the grid network, can offer residual capacity to the balancing markets on a 15 minutes basis, a so-called program time unit (PTU). Each PR firm reports to TenneT in an energy program the amount of electricity to be supplied to and consumed from the grid for the 96 PTU's on the following day. Whilst balance-management capacity should be available for TenneT within 15 minutes, it is either contracted in advance or offered on a voluntary basis via the balancing market. PR firms with more than 60 MW of capacity are obliged to offer reserve capacity to the balancing market. In particular, on the imbalance market, TenneT act as a single-buyer or seller. In cases of balancing deficits, PR companies balancing residual capacity offer price quotes to TenneT. TenneT purchases the volume needed against the best prices. The price of this balancing volume is charged to the PR that caused the deficit the day after. In cases of balancing surpluses, TenneT sells power to PR companies against quoted ask prices. Therefore, TenneT reports two balancing prices, one price for volume deficits and one for power surpluses.

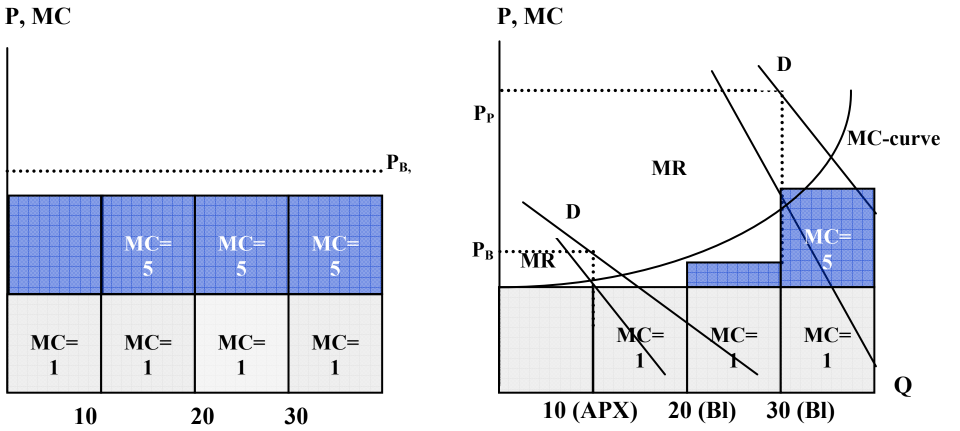
2.3.2 The balancing market price mechanism

In textbox 2.2a we have illustrated the traditional system where prices were regulated. For the sake of illustration we assume a world that consists of two types of plants: power generators (G1) with low marginal cost (MC=1), and more expensive power generators (G2) with high marginal costs (MC=5). Before the deregulation was imposed, prices reflected the weighted[16] average costs of generation, transmission and distribution. This is in contrast with the current market system, which reflects the marginal cost curves of the individual suppliers (see textbox 2.2b): Economic theory states that in a competitive market, the market delivers prices close to short-run marginal costs. [17] A change in the allocation system due to the imposed deregulation will therefore be directly observable in the dynamics of prices.

[16] Weighted relative the total installed production capacity.

[17] Only in a perfect competitive market prices equal marginal costs. It is a well-known fact that in oligopolistic markets (with few dominant suppliers but many consumers, such as the electricity industry), prices cannot be fully explained by its fundamentals (i.e marginal cost curves). A substantial fraction of the academic research on price behavior in power markets has concentrated on the presence of market power (e.g. when suppliers would exercise market power, prices would be higher than suggested by the marginal cost curves).

To see why this is true, let us examine the market allocation system of the APX. Here power suppliers deliver their bidding scheme to the exchange, in which they specify that they are willing to offer against different prices for next-day delivery of power. When prices are low, only the bids of suppliers that can generate power against low marginal costs (or suppliers that have previously entered into purchasing contracts that secure them the power delivery against low prices) are confronted with purchase orders. The supplied volume increases when the price rises to a level that is higher than the short-term marginal costs of the first upcoming supplier in the merit-order.



: G1 power plant, subscripts B,(P); Base, (Peak)
: G2 power plant, P: Prices, Q: Quantity,
D: Demand MC (/MR): Marginal Costs
(/Revenues) Bl:Balancing

2.2a. Regulated price agreements 2.2b. APX, balancing market

Textbox 2.2: Dutch market mechanisms from 1998-2003
(corresponding with bold blocks of textbox 2.1)

The merit-order ranks suppliers based on their offered capacity in such a way that the bids of suppliers with the lowest short-term marginal costs are confronted with demand first. If a market becomes more allocative efficient, the merit-order[18] on the day-ahead market implies that the cheaper generation facilities generate most of the consumption needed.
Also on the balancing market this allocation principle is effective: The transmission system operator collects the bids and ranks them on increasing price level. The market price is set equal to the highest bid for the total capacity needed to offset the unbalanced position.[19] Balancing volumes are traded on the balancing market that operates on the day of delivery, thus one day after the prices on the day-ahead market have been set. Hence, in allocative

[18] See the website of TenneT (www.tennet.nl) and the APX (www.apx.nl) for more details about the merit-order based pricng system that is implemented on both the day-ahead and balancing market.
[19] This allocation system applies two both sides (deficit and surplus side) of the bid price ladder.

efficient markets, the unbalance deficit volume, i.e. the volumes needed to overcome shortages, should come from the more expensive production facilities as the cheaper ones already operate fully due to the merit order of the day-ahead market. If the Dutch power market becomes more allocative efficient, then we expect the deficit prices on the balancing market to show an upward trend as the more expensive generators are allocated to deliver electricity via the balancing market, in case imbalance on the power grid. The merit-order system of the market implies that the bidder with the lowest marginal costs gets the purchase order, hence this mechanism is in accordance with the principle of allocative efficiency as defined in the previous section.

2.3.3 Hypotheses 1 and 2

From textbox 2.2b we see that if the Dutch power market becomes more allocative efficient, the deficit prices on the balancing market are expected to increase over time as the more expensive power plants are allocated to deliver power via the balancing market.
Our first hypothesis reads as:
H1: "the deficit prices on the balancing market are expected to increase over time"

In order to test this hypothesis we analyse the dynamics of the deficit prices over time. We estimate the parameters from the following equation:

$$P(t) = \alpha+\beta\, P(t-1) + \gamma t + \varepsilon(t), \quad \varepsilon(t) \sim IID\,(0, 1) \tag{2.1}$$

From equation 2.1, we can see that we model the dynamics of the deficit price level P(t) as an AR(1) process with a trend variable t that equals 1 for the first 15 minutes in our sample, 2 for the second 15 minutes and so forth. We use price levels instead of natural logarithms as unbalancing prices can become negative. We included the trend term to test directly for a price increase over time, by interpreting the estimate for γ. Evidence that γ is significant and positive, would imply that hypothesis 1 is empirically supported.

We also control for the possibility of fuel price increases (e.g. gas, oil or coal price increase) that may drive prices on both the APX and balancing market to higher levels. We therefore replace the dependent variable P(t) in equation 2.1 by the variable PD. To do this, we calculate PD as the difference between the balance deficit price and the APX price. Since the deficit prices are quoted on a 15 minutes frequency, we convert these prices to daily averaged prices. We denote this daily average price over 96 balancing price observation as P'(t). An important point worth emphasizing is that the APX price is realized on the day before delivery. By testing our hypothesis also on the price spread, we also correct for these fuel price effects. We rewrite 2.1 as:

$$PD(t) = \alpha+\beta\, PD(t-1) + \gamma t + \varepsilon(t), \text{ where } PD = P'(t) - APX\,(t-1)\,,\ \varepsilon(t) \sim IID\,(0, 1) \tag{2.2}$$

Evidence that γ is significant and positive, would imply that hypothesis 1 is empirically supported.
We now focus on the balancing volumes, which are indicators for security of supply as discussed in section 2.2.1. The existence of the day ahead APX and real-time balancing market makes that the incentives are created for accurate supply-demand matching for expected demand and unexpected demand. If the markets become more allocative efficient, energy firms have improved capabilities to make demand expectations. This should lead to

lower unbalance volumes. If the Dutch market becomes more allocative efficient, we expect balancing volumes to decline. The second hypothesis in our study is:

H2: “the volumes on the balancing market are expected to decrease over time”

We estimate the parameters in a similar model as in equation 2.1. We replace the dependent variable in equation 2.1 by V(t). Here V(t) is the unbalance volume, respectively surplus, deficit, absolute or net balance volume.

We estimate the parameters from the following equation:

$$V(t) = \delta + \lambda V(t-1) + \theta t + \varepsilon(t), \quad \varepsilon(t) \sim \text{IID}\ (0, 1) \tag{2.3}$$

2.4 Sample and data description

We obtain balancing prices and volumes from the TenneT website (www.tennet.nl).

	Price		Volume			
	Surplus	Deficit	Surplus	Deficit	Absolute	Net
Mean	4.244	82.29	48.33	61.46	109.8	13.13
Median	7.150	45.45	40.24	54.16	97.25	12.53
Std deviation	38.19	113.3	36.31	38.81	62.36	41.95
Minimum	-222.0	-100.0	0.005	0.019	19.02	-327.3
Maximum	1754	1984	583.2	574.1	1106	405.5
Skewness	9.449	6.591	3.695	3.696	5.023	0.333
Kurtosis	370.8	77.80	31.05	29.72	51.61	9.808

Absolute (unbalance) is the sum of the surplus and deficit volumes.
Net (balance) is the difference between deficit and surplus volumes.

Table 2.1: Descriptive statistics of balancing prices (€/MWh) and volumes (MW) in 2002 – 2003.

TenneT started with publishing this data as of the year 2002. Our sample therefore consists of 70080 observations of 15 minutes observations from 1 January 2002 to 31 December 2003.

From table 2.1, we can see that on average the surplus prices are lower than the deficit prices. In cases of power deficits, TenneT purchases on average against a price of €82 p/MWh, whereas it sells in cases of surplus against €4 p/MWh. The standard deviation of the price levels equals €38 p/MWh in cases of surpluses and €113 p/MWh in cases of deficit. Note that negative prices exist as can be seen from the minimum price levels. This is due to the fact that PR companies have to pay large fees for serious surpluses or deficits. They are willing to pay any price below the fee level to overcome paying the fee. The average surplus volume is lower than the average deficit volume, which leads to an average net positive unbalance.

The descriptive statistics of the daily averaged deficit price P'(t), the daily APX prices and the price spread PD, are listed in table 2.2.
P'(t) is calculated as the daily average over 96 quarter-hourly deficit price observations. The data now consists of 730 observations from aforementioned sample period.

	P'(t)	APX	PD(t)
Mean	74.60	58.23	36.40
Median	61.08	28.77	29.30
Std deviation	54.70	44.17	54.74
Minimum	16.91	8.599	-521.83
Maximum	820.3	660.34	801.14
Skewness	5.799	8.590	2.694
Kurtosis	62.88	107.26	73.08

Table 2.2: Descriptive statistics of daily average deficit price, APX price and price spread (€/MWh) in 2002 - 2003.

From table 2.2 we can see that PD(t) has a positive mean value equal to €36.40 p/MWh. This is consistent with our reasoning that the cheaper power generators are allocated to the APX, while the more expensive generators deliver electricity on the imbalance market the following day.

2.5 Results

An informal look at the aggregated deficit imbalance prices of the year 2002 and 2003, suggests that the allocative efficiency on the Dutch power market has increased; this price was €63 p/MWh in 2002 and €102 p/MWh in 2003, which is an increase of 60%. In addition, the net imbalance volume decreased with 40% from 16.4 MW in 2002 to 9.9 MW in 2003. Although these figures give a first indication that efficiency increased, we still need to formally test the hypotheses that we proposed in section 2.2.3. We do this by modeling the imbalance prices and volumes by equation 2.1 to 2.3.

2.5.1 Results for hypothesis 1

Table 2.3 provides the OLS estimation results for equations 2.1 and 2.2.
We observe the positive and significant estimate for the parameter γ that is the coefficient for the trend variable in equation 2.1. The estimated value of 0.0001 is low, but reflects the average price increase over 15 minutes intervals over a two-year time period. We

furthermore see that the trend variable γ in equation 2.2, when correcting for the APX price to control for changes in the generators' fuel mix, is positive and significant. The value of 0.0439 implies that the increase is €0.0439 per day.

	Equation 2.1	Equation 2.2
α	5.0298 (1.09749)***	13.889 (2.23272)***
β	0.8670 (0.02012)***	0.1239 (0.07084)*
γ	0.0001 (0.00002)***	0.0493 (0.00939)***
Adjusted R^2	0.7762	0.0612
ADF test statistic	-26.9993***	-12.8721***
Number of obs.	70080	730

Newey-West standard errors are in parentheses. Significant at: ***99%, **95%, *90% confidence level. Critical value of ADF tests is -3.434 (equation 2.1) and -3.442 (equation 2.2).

Table 2.3 Ordinary Least Squares results for equations (2.1) and (2.2)

This confirms our hypothesis (H1) that the deficit prices in the unbalance markets have increased over time due to improving allocative efficiency. In order to examine whether the $\varepsilon(t)$ exhibit high-order serial correlation, we apply the Ljung-Box autocorrelation test. The Ljung-Box Q-statistic at lag k is a test statistic for the null hypothesis that there is no autocorrelation up to order k. Under the null hypothesis it is asymptotically distributed as a Chi-square distribution with the degrees of freedom equal to the number of autocorrelations. The Ljung-Box test results obtained from the residuals of equation 2.1 disclose that the residuals do exhibit autocorrelation[20]. From the Ljung-Box test result obtained from the residuals of equation 2.2 we conclude that the residuals are not serial autocorrelated (up to lag 1)[21]. Note that we report the standard errors proposed by Newey and West (1987) to control for both serial correlation and heteroskedasticity in the error term.

To guard against the possibility of interpreting misleading results, we must be sure that the residual process of equation 2.1 is not a random walk. We therefore employ the Augmented Dickey Fuller (ADF)-test to find evidence for the existence of a random walk

[20] The Ljung-box Q statistics for lag 1 to 4 are: 100.1 (0.000), 212.6 (0.000), 218.8 (0.000) and 369.7 (0.000). P-values are in parentheses. Here we report Q statistics up to lag 4, which translate to a one-hour time lag.

[21] The Ljung-box Q statistic for lag 1 is: 0.279 (0.597). Here we report a Q statistic up to lag 1, which translate to a one-day time lag.

in the error process ε(t). Evidence of a unit root implies that the residuals are non-stationary, henceforth this would imply that we can not rely on the estimates provided.
From the table, we can see that the ADF test statistics are both lower than the critical values at the 99% confidence level. We reject the null-hypothesis that the error processes in equation 2.1 and equation 2.2 have a unit-root. This implies that the results provided are statistically reliable.

2.5.2 Results for hypothesis 2
If the markets become more allocative efficient, energy firms have improved capabilities to make demand expectations. This should lead to lower unbalance volumes. A decreasing trend in balancing volumes goes in line with improved allocative efficiency. We therefore test hypothesis by modeling equation 2.3. The results are provided in table 2.4.

Table 2.4 shows the negative and significant coefficient for the trend variable θ, for all volumes V(t) considered.

	V(t) Surplus	V(t) Deficit	V(t) Absolute	V(t) Net
δ	6.1717*** (0.156626)	10.1707*** (0.69085)	8.2972*** (0.753369)	5.3847*** (0.306795)
λ	0.8929*** (0.001701)	0.8734*** (0.010099)	0.9399*** (0.00635)	0.7633*** (0.00954)
θ	-0.00003*** (0.000003)	-0.00007*** (0.000004)	-0.00004*** (0.000003)	-0.00006*** (0.000006)
Adjusted R^2	0.8017	0.7817	0.8913	0.5899
ADF test statistic	-37.5714***	-33.228***	-28.553***	-49.484***

Newey-West standard errors are in parentheses. Significant at: ***99%, **95%,
*90% confidence level. Critical value of ADF test is –3.4337. Number of observations: 70080

Table 2.4 Ordinary Least Squares results for equations (2.3)

Although the levels are low, reflecting the average decline over a 15 minutes interval over a two-year time period, it is observed that all unbalance volumes decrease over time.
From the ADF test on the V(t) series we reject a unit root at the 99% confidence level in the error term of each individual estimation, which implies that we can seriously interpret the provided results. The Ljung-Box Q-statistic at lag k is a test statistic for the null hypothesis that there is no autocorrelation up to order k.

We employ the Ljung-Box test on the residuals of each of the four volume time series, which show that each of the four noise terms exhibit autocorrelation[22]. Note that we report the standard errors proposed by Newey and West (1987) to control for both serial correlation and heteroskedasticity in the error term.
This result confirms our hypothesis (H2) that unbalance volumes should decline due to increasing allocative efficiency. The decreased dependency from the imbalance market is an indication for increased security of supply in the Dutch power market.

2.6 Concluding remarks

This Chapter provides evidence that the balancing price- and volume trends observable on the Dutch power markets are in accordance with a higher level of allocative efficiency. We find that unbalanced prices increased and that unbalance volumes declined. The price increase can be explained by allocative efficiency as cheaper production facilities are allocated in the merit-order of the day-ahead market and that only more expensive production facilities are available for unbalance volume. The volume decrease can be explained by improved demand forecasts of energy firms, which leads to fewer shocks to the system. This has a positive effect on the security of supply as long as a minimum reserve level is maintained. Although our analysis covers only part of the market, we claim that the documented result provides at least partial evidence of a successful liberalisation process of the Dutch electricity market.

[22] The Ljung-box Q statistics for lag 1 to 4 are 451.9 (0.000), 1837.1 (0.000), 1952.1 (0.000), 11458 (0.000) for the V(t) deficit noise term. 762.6 (0.000), 3035.0 (0.000), 3327.0 (0.000) and 9259.8 (0.000) for the V(t) surplus noise term. 1321.2 (0.000), 3169.7 (0.000), 3205.7 (0.000) and 5461.9 (0.000) for the V(t) all noise term. 638.8 (0.000), 1257.9 (0.000), 2321.8 (0.000), 3753.8 (0.000) for the V(t) net noise term. P-values are in parentheses. Here we report a Q statistics up to lag 4, which translate to a one-hour time lag.

Chapter 3: Fat tails in daily electricity spot prices[23]

-Empirical study on the Dutch day-ahead market-

3.1 Introduction

In this Chapter, we focus on the daily day-ahead electricity prices obtained from the Dutch APX market. As discussed in the previous chapter, on the APX separate prices are quoted for delivery in each specific hour in the next day; the daily average is then the average over the 24 hours. Many day-ahead markets distinguish daily average baseload prices, which refer to the average price over all 24 hours. On some markets, such as Australia, New Zealand and the United Kingdom, prices are even quoted on a half-hourly basis.

It is commonly known that electricity market prices for day-ahead delivery exhibit mean reversion, seasonality and spikes. These stylised facts affect all market participants in their risk exposure to spot prices. Appropriate pricing and risk management models should incorporate these facts.

The traditional models[24] for electricity spot price dynamics focus mostly on mean reversion and seasonal patterns. Spot prices of electricity are modelled as the sum of a deterministic component that captures seasonality and a stochastic component that captures mean reversion and a noise term. This error term is mostly assumed to be normally distributed or at least to be independently and identically distributed (IID). These models do not capture one of the most important characteristics of power prices being the frequent occurrence of spikes. For example, the average Dutch price of electricity was about €30/MWh in 2002 and a maximum price has occurred in 2002 of €701/MWh between noon and 3 pm on August 21st, 2002. In 2001, the maximum baseload price equalled €220/MWh. Graph 2.1 presents the daily prices of baseload electricity (whole day delivery) for 2002.

Monte Carlo simulations based on the traditional models do not resemble the actual price patterns of spot power. As practitioners frequently use these simulations for risk management and valuation purposes, it is clear that researchers should improve upon the traditional models.

Motivated for reasons discussed above, models have been introduced recently that focus more closely on the spike characteristics. For example, jump processes and switching regime models have been introduced to model spikes in spot prices, thereby directly affecting the third and fourth moment of the noise term: See Deng (1999), de Jong and Huisman (2002) and Huisman and Mahieu (2003) among others. The advantage of these approaches is that they explicitly model the spikes and therefore allow for non-normal characteristics. Furthermore, switching regime models have the advantage of not affecting the estimates of the level of mean reversion as these models disentangle the mean-reversion from spikes from normal periods. However, in switching regime models more parameters are needed (compared to any of the aforementioned models) to describe the price dynamics accurately.

In this Chapter, we concentrate on the tail characteristics of the error term. We apply extreme value theory (EVT) to assess the level of tail fatness. EVT investigates the

[23]This Chapter is based on: R. Huisman and C. Huurman, 2003, "Fat tails in power prices", ERIM Report Series, July, Rotterdam. We thank participants at the Quantitative Methods in Finance Conference in Sydney (9 – 13 December 2003) for valuable comments.

[24] Examples are discussed in Pilipovic (1998) and Lucia and Schwartz (2002) among others.

extreme movements in tails of the price change distribution, in our study the tails of the noise term. Applications can be found in the areas of engineering and finance among others.[25] We test whether EVT can directly be applied to replace the normality assumption for a different distribution. We propose the Student-t distribution as an alternative, and then demonstrate how to apply this distribution for Monte Carlo simulations. The advantage of the Student-t distribution compared with the normal distribution is that it captures tail fatness through its degrees of freedom parameter that can be calibrated by EVT. In this method, spikes are captured through the selection of the distribution function. Our simulation results clearly improve upon the ones from the normal distribution, as the Student-t price patterns resemble more closely the true price pattern of daily power spot prices.

The remaining part of this Chapter is structured as follows. In section 3.2 we discuss the methodology. Section 3.3 provides the data. In section 3.4 we present and discuss the results. Section 3.5 concludes.

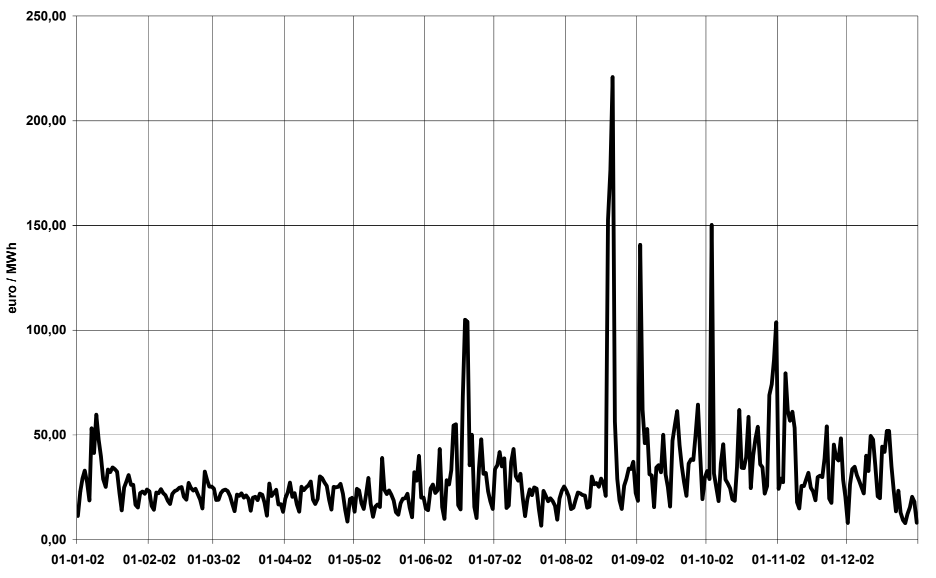


Figure 3.1: Baseload prices for Dutch day-ahead delivery of electricity for 2002

3.2 Methodology

In this study we employ the EVT tail estimator proposed by Huisman et al. (2001) that has the advantage compared to other often-used estimators that it is unbiased in small samples. The rationale to adopt their estimator is due to the observation that competitive electricity markets exists since recently. In section 3.2.1, we provide a concise summary of the tail estimator methodology of Huisman et al (2001). We refer to that study for more details on

[25] See Embrechts et al (1997).

the econometric considerations. In section 3.2.2 we present the electricity price model from which we derive the noise term. Henceforth, this model provides the input for our EVT analysis.

3.2.1 Extreme value theory

The major advantage of applying EVT on electricity price model residuals is that we can directly model the extreme price movements that we can observe in electricity markets. EVT namely allows us to model the tails directly, hence not as an indirect result of modelling the whole distribution. In addition, when an investor is interested in the chance of occurrence of an extreme price event (as part of her risk assessment), the information obtained from the variance of the price distribution may be insufficient; a price series that is characterized by a tranquil price path that embeds only a few very extreme price events may have a higher volatility parameter than a price series that incorporates more frequent extreme price movements.

It is a well-known fact that distributions of many financial assets exhibit tail fatness. Hence, this distributional feature is not only observable in power prices.[26]

The classic EVT puts forward an ideal framework to identify tail fatness. It can be divided into two streams: (1) the block-maxima method, which divides the data into consecutive blocks and focusing on the series maximum values in these blocks (Embrechts et al., 1997). (2) Alternatively the extreme price observations (in our case model residuals) can be modelled over a certain threshold. This approach is known as the peak-over-threshold method (Balkema and De Haan, 1974). We assess the level of tail fatness of the model's residuals by using the latter mentioned method.

Huisman et. al. (2001) estimator

The Hill (1975) is a widely used estimator for the tail-index. The tail index is a measure for the amount of tail fatness of the distribution under investigation and may also be looked upon as an indicator for the pace with which the tail moves to zero. The fatter the tail, the slower the speed and the lower the tail index given. The Hill estimator reads as:

$$\gamma(k) = 1/k \sum_{j=1}^{k} \ln(x_{n-j+1}) - \ln(x_{n-k}) \qquad (3.1)$$

Here $\gamma(k)$ is the tail-index that is a function of the number of tail observations k, and n is the number of sample observations. Note that the inverse of $\gamma(k)$, equals the maximum number of existing finite moments α. The Hill estimator, and many other EVT tail estimators that have been introduced since Hill's epic work, suffer from a small sample bias (For an overview see Pictet et. al., 1996). The bias in these estimators is caused by the fact that the choice of the amount of tail observations (k) to include in the estimation is arbitrary: On the one hand when one includes too few observations, the estimate is unbiased but becomes inaccurate. That is, the variance of the estimate becomes too high. On the other hand, inclusion of too many observations may lead to an estimator that is derived by partly using center observations, which we are clearly not interested in. Huisman et. al. (2001) show that the bias in the Hill estimator can be approximated by a linear function of the tail observations (k) used in the estimation. Here the threshold level k

[26] See Huisman et al. (1998) for bond and stock portfolios, Boothe and Glassman (1987) for exchange rates, and Campbell and Huisman (2003) for credit spreads.

is chosen such that linearity applies. Following Huisman (2001), we set k equal to half of the sample size (this is to ensure that the estimator is robust). The estimator that they propose is a weighted average of a set of traditional Hill estimators. The weights are estimated by using weighted least squares techniques. Their estimator proves to be robust for a sample as small as 100 observations.

$$\gamma(k) = \beta_0 + \beta_1 k + \varepsilon(k) \tag{3.2}$$

Here β_1 yields the unbiased tail estimate. The inverse of this estimate equals the true tail index α. The tail index has the attractive feature that it is equal to the number of existing moments of the distribution and thus can be used to parameterise the Student-t distribution.

Student-t distribution

Huisman et al (2001) propose to use the Student-t distribution as an alternative to the normal distribution as its shape is taller in the middle and as it is capable of incorporating fat tails. Following Huisman et al (2002), we examine to what extent the Student-t distribution would provide a better fit than the normal distribution function. In order to examine the appropriateness of the Student-t distribution, we have to estimate the degrees of freedom parameter α. The standardized Student-t distribution is a symmetric distribution and it's being shaped by one parameter: the degrees of freedom α. The standardized Student-t distribution has zero mean and its variance equals α / (α-2). An important property of the Student-t distribution is that it converges to the normal distribution for $\alpha \rightarrow \infty$. The degrees of freedom α equals the number of existing moments and α is directly related to the tails of the distribution function. For high values of α, the distribution has tails that corresponds closely with the normal distribution, but the lower α gets, the fatter the tails become. Huisman et al. (2002) show that α is between 3 and 8 for different exchange rates. The procedure that we follow involves estimating the tail index from the empirical distribution. Before we can formally test whether the Student-t distribution provides a better fit than the normal distribution, we first need to re-scale the standard deviation of the residual distribution. The variance of the standardized Student-t distribution is namely not equal to 1, in contrast with the variance of the normal distribution. Let x be the residual under consideration. To fit the student-t-distribution we assume that $y = \varphi(x - \rho)$ is Student-t distributed with α degrees of freedom. Here ρ is a location parameter that equals the residuals mean, which is zero. The scale parameter φ is a function of the variance (var):

$$\mathrm{Var}\,(y) = \alpha / (\alpha - 2) = \varphi^2\,\mathrm{var}(x) \tag{3.3}$$

When we rearrange the terms of equation (3.3), we get:

$$\varphi = \sqrt{(\alpha / (\alpha - 2)\,\mathrm{var}\,(x))} \tag{3.4}$$

To formally test the hypothesis that the fitted Student-t distribution is a good approximation for the unconditional empirical distribution of the residuals obtained from the price model (we will present our electricity price model in the next subsection), we apply the goodness of fit-test following Boothe and Glassman (1987) and Huisman et. al. (2002). The goodness-of-fit test compares the observed and expected number of observations in c intervals over which the data is divided as follows:

$$G = \sum_{j=1}^{c} \frac{(o_j - e_j)^2}{e_j} \tag{3.5}$$

Here o_j and e_j are the observed and expected number of (tail-quantile exceedness) observations in interval j. The test statistic G is Chi-squared distributed with (c-1) degrees of freedom. The intervals (except the first in the left tail and the last in the right tail that range to minus or plus infinitely respectively) are chosen such that they are of equal length. Note that each interval has at least five expected observations, which is to ensure that the Chi-squared approximation is accurate.

3.2.2 Day-ahead power price model

Following Lucia and Schwartz (2002) and Huisman and Mahieu (2003), we model daily electricity prices by decomposing the log day-ahead power price s(t) at time t (t = 1,2,…,T) as the sum of two independent components: A deterministic component, f(t), and stochastic component, x(t):

$$s(t)= f(t) + x(t) \tag{3.6}$$

Introducing Δ as the differencing operator, we can write the daily changes in the log price of power as:

$$\Delta s(t)= \Delta f(t) + \Delta x(t) \tag{3.7}$$

The component f(t) is a deterministic function of time and models predictable regularities, such as periodic behaviour and trends. Let f(t) account for the fact that the price for electricity delivered on weekend days is lower than the price on an average working day. To do so, we introduce two dummy variables: D1(t) equals 1 on Saturdays and 0 on other days and D2(t) equals 1 on Sundays and 0 on other days. We therefore specify f(t) as follows:

$$f(t) = \mu + \beta_1 D_1(t) + \beta_2 D_2(t) \tag{3.8}$$

In equation (3.9), the parameter μ reflects the average log price level.
As mentioned earlier, electricity prices observed in some markets exhibit seasonal behavior.[27] Although no rationale exists for expecting seasonality in Dutch power prices (mild climate and no season-dependent generation[28]), we test for seasonal behavior. The results of this seasonality test can be found in the Appendix (A.3.2, A3.3). Based on these results, we rely on equation (3.8) as an accurate description of the predictable regularities in this market. The stochastic component x(t) in equation (3.7) reflects the movement of the electricity price out of its deterministic behaviour at time t. One important characteristic is mean reversion. Following Pilipovic (1998), let α be the speed with which the spot price of power reverts back to its long term mean. As the long-term mean μ is

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[27] For instance, power prices in the Scandinavian market exhibit seasonality (Lucia and Schwartz, 2002). Here, seasonality stems from the fact that this is a hydro-power market. Water is stored in reservoirs and the water level rises in the summer when snow is melting. As a result, power prices are lower in summer than in winter. In other markets, seasonality in power prices is due to seasonal behavior on the demand-side; i.e. the use of air-conditioning systems (Eydeland, 2003).

[28] See table 1.1: 95% conventional thermal generation in The Netherlands.

captured by the deterministic component in equation (3.8), we model mean reversion in the stochastic part as reversion due to a deviation from 0:

$$\Delta x(t) = -\alpha\, x(t-1) + \sigma\, \varepsilon(t), \quad \varepsilon(t) \sim IID\ (0, 1) \tag{3.9}$$

Here $\varepsilon(t)$ represents the noise term and σ the standard deviation of this noise term. After substituting equations (3.9) and (3.8) into equation (3.7), we come to the following model for daily log price changes of power:

$$\Delta s(t) = \alpha\mu + \beta_1\ \{D_1(t) + (\alpha-1)\ D_1(t-1)\} + \beta_2\ \{D_2(t) + (\alpha-1)\ D_2(t-1)\} - \alpha\ s(t-1) + \sigma\ \varepsilon(t) \tag{3.10}$$

Above equation did not generate white noise model residuals (white noise means a noise term that is homoskedastic and exhibits no autocorrelation); we find that autocorrelation is clearly apparent for the 7th lag, which can be explained as a weekly pattern in power prices. We therefore have included an autoregressive term in equation (3.11) to control for this. Now equation (3.10) becomes:

$$\begin{aligned}\Delta s(t) = \alpha\mu &+ \beta_1\ \{D_1(t) + (\alpha - 1)\ D_1(t-1)\} + \beta_2\ \{D_2(t) + (\alpha - 1)\ D_2(t-1)\} - \alpha\ s(t-1) \\ &+ \theta\Delta s(t-7) + \sigma\ \varepsilon(t)\end{aligned} \tag{3.11}$$

We will report the parameter estimates of equation (3.10) in Appendix (A.3.3), and the model (3.11) coefficient in the next section, since only latter mentioned model is used for the data-generating process in our study. We apply non-linear least squares (NLS) to estimate the parameter value, since equation 3.11 is non-linear in its parameters.

Limit of proposed method

The two-steps method (we first estimate the NLS parameters of equation 3.11 and then impose a Student-t distribution on the models residuals) that we propose in this section can be considered as a diagnostic test to show that the Student-t distribution is capable of correctly capturing the fat tailed behaviour of electricity prices opposed to the often-assumed normal distribution. We are aware that re-estimation of the parameters of equation 3.11 by using maximum likelihood techniques that allows us to impose a Student-distribution on the residuals directly, would yield conclusive results of our proposed methodology. [29]

3.3 Data and sample description

The data used in this Chapter is derived from the Amsterdam Power Exchange (APX).
We use baseload prices from 1 January 2001 through 22 July 2003 being 933 daily price observations. Table 3.1 provides an overview of summary statistics of this data in price levels, log prices and log price changes. Table 3.1 discloses the non-normal characteristics of the data being the positive skewness and excess kurtosis. Positive skewness is due to the fact that the occurrence that power prices are extremely high is more probable than the chance of occurrence of low extreme prices. The kurtosis estimate value is around 7 for log power prices and is significantly higher than 3, the kurtosis value of a normal distribution. This implies that extreme price movements are more likely to occur than indicated by the normal distribution. Both characteristics are well-documented facts of day-ahead power prices.[30]

[29] In our proposed method we implicitly assume that the t-distributed noise term is uncorrelated with the other model parameters.
[30] See a.o. Pilipovic (1998) and Bessembinder and Lemmon (2002).

	Price level	Log price	Log price changes
Mean	32.69	3.338	0.004
Median	26.92	3.293	-0.023
Std. deviation	25.04	0.500	0.477
Minimum	1.480	0.392	-2.372
Maximum	263.1	5.573	2.769
Skewness	4.679	0.638	0.687
Exc. kurtosis	32.22	7.182	7.192

Table 3.1: Descriptive statistics for daily APX baseload prices (€/MWh)

3.4 Results

Below we present the empirical results.

3.4.1 Model estimates

In table 3.2 we provide the equation (3.11) NLS parameter estimates. We apply non-linear least squares (NLS) to estimate the parameter value, since the equation is non-linear in its parameters. Note that the standard errors are based on the estimator of the covariance matrix proposed by Newey and West (1987) and therefore controls for both serial correlation and heteroskedasticity in the error term.

μ	3.479 (0.033)***	θ	0.080 (0.032)**	Jarque-Bera	1034.3
β_1	-0.303 (0.030)***	σ	0.324	White	9.481
β_2	-0.646 (0.030)***	Adj R^2	0.515		
α	0.360 (0.026)***	SIC	0.622		

Newey-West standard errors are in parentheses. Significant at: ***99%, **95%, *90% confidence level. The estimate for μ of 3.479 relates to a long-term average price of €32.43/MWh. SIC (Schwartz Information Criterion). Number of observations: 933

Table 3.2: NLS parameter estimates and residual characteristics for equation (3.12).

From table 3.2, we observe a long-term average log price of 3.479, which is 0.303 lower on Saturdays and 0.646 lower on Sundays. The estimate for the speed of mean reversion equals 0.36 and is significant. From table 3.2 we observe the significance of the lagged term (indicated by significant θ coefficient). Let us now concentrate on the characteristics of the noise term. The Jarque-Bera statistic is a test for normality. Under the null hypothesis it is distributed as a Chi-square distribution with two degrees of freedom. The

Jarque Bera test statistic that we find is much higher than its critical value of 5.99 (95% confidence level). Therefore, we reject the hypothesis of normally distributed residuals. The White statistic is the outcome of a White test on homoskedasticity of the residuals (including cross-terms). The critical value at the 95% confidence level is 15.51. The lower value of 9.481 for White makes that we cannot reject the null-hypothesis of homoskedasticity for the residuals. In order to examine whether the residuals exhibit high-order serial correlation, we apply the Ljung-Box autocorrelation test. The Ljung-Box test for autocorrelation does reject the hypothesis that the residuals exhibit autocorrelation[31]. We conclude that the residuals of equation 3.11 are IID but not normal. This is in contrast with many proposed models that are being used especially for Monte Carlo simulations. In these cases, one assumes a data-generating model for the spot price development over time (such as model 3.11), in which the daily innovations $\varepsilon(t)$ are drawn from a particular distribution. In many cases, the normal distribution is chosen for reasons of convenience. But the drawback of this convenience can be enormous as one has an erroneous assessment of the true risks faced because of the fact that he or she neglects the non-normal properties of the innovations. Especially for electricity prices, these non-normal properties are pronoun.

Figure 3.2 shows the histogram of the residuals and the fitted normal distribution function. The figure shows clearly that the normal distribution provides a poor fit to the histogram of the residuals. Not only in terms of tail fatness, but also for the probability mass in the middle as we see that the frequencies in the middle are much higher for the actual data than what the normal distribution would imply.

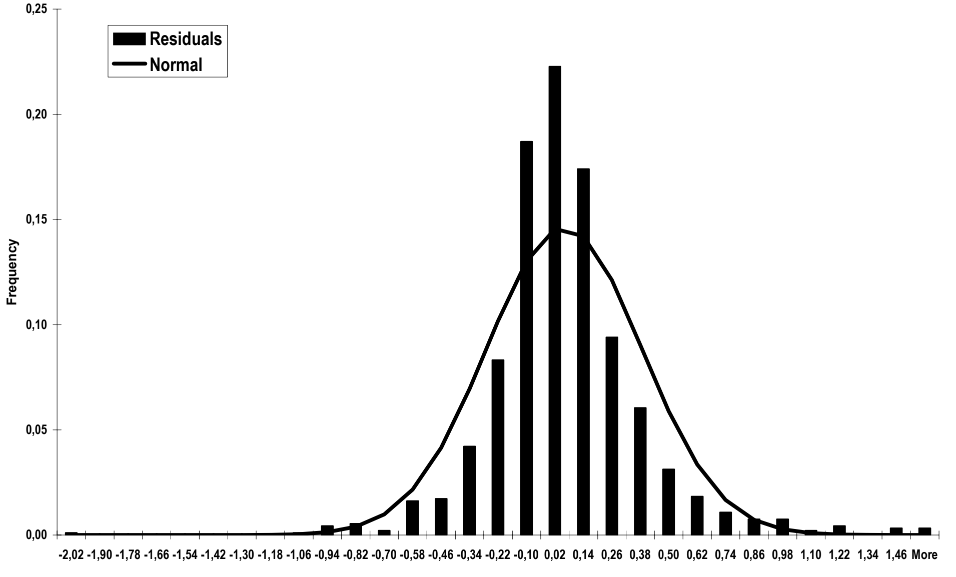

Figure 3.2: Histogram of the residuals from equation (3.11) and the fitted normal distribution.

31 The Ljung-box Q statistics for lag 1 to 7 are: 1.602 (0.109), 1.904 (0.168), 1.975 (0.373), 3.611 (0.307), 5.531 (0.239), 8.131 (0.149) and 8.466 (0.206). P-values are in parentheses.

3.4.2 Tail index estimates

As said, the tail index is a measure for the amount of tail fatness of the distribution under investigation. The index can be regarded as an indicator for the pace with which the tail moves to zero: the fatter the tail the slower the speed and the lower the tail index given. Table 3.3 shows the tail index parameter estimates for the residuals from equation (3.11).

Both tails	3.182 (0.003)
Left tail only	3.142 (0.005)
Right tail only	3.331 (0.004)
Standard errors are in parentheses	

Table 3.3: Tail index estimates for the residuals of equation (3.11)

3.4.3 Goodness-of fit test

Now we have estimated the degrees of freedom parameter α, we investigate whether the Student-t distribution is able to provide a better fit than the normal distribution to the residuals of equation (3.11). First we re-scale the σ of the residual distribution by using equation 3.4, to make comparison between both distributions possible. We then apply the obtained tail index to parameterize the Student-t distribution. We set the degrees of freedom parameter equal to 3.142 (taken from table 3.3), and φ equal to 5.113 (obtained from equation (3.4). We then can plot the histogram of the residuals and the Student-t fit, which is depicted in figure 3.3.

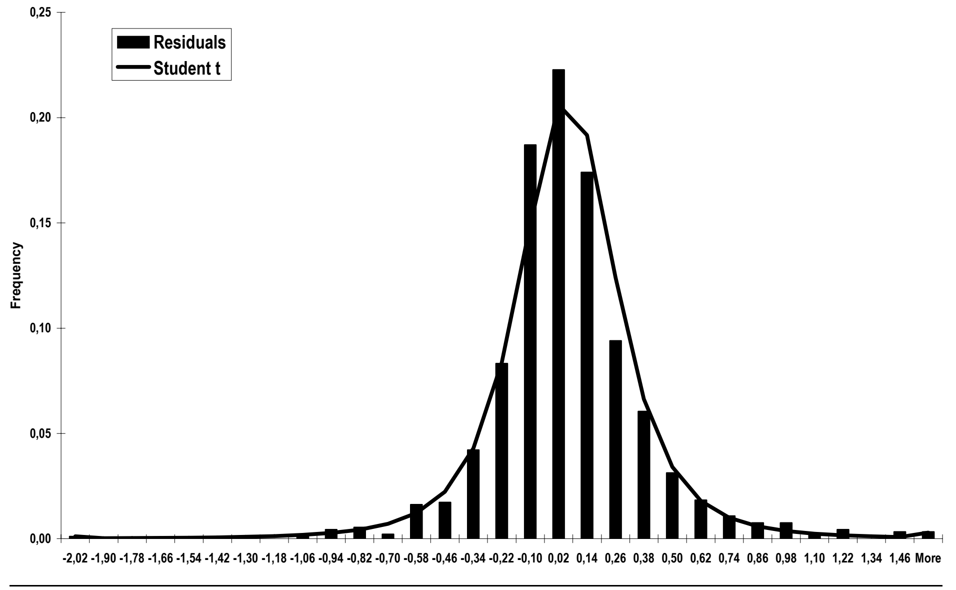

Figure 3.3: Histogram of the residuals from equation (3.11) and the fitted Student-t distribution.

At first glance, the student-t distribution seems to graphically fit the complete empirical distribution of residuals very well for the residuals. Compared with the fit from the normal distribution shown in figure 3.2, we obtain a better fit for the tails and for the central part of the distribution. To formally test the hypothesis that the fitted Student-t distribution is a good approximation for the unconditional empirical distribution of the residuals, we apply the goodness of fit-test given by equation (3.6).
Table 3.4 contains the goodness of fit results for the normal distribution and the Student-t distribution. According to the goodness-of-fit results in table 3.4, we cannot reject the hypothesis that the Student-t distribution provides a good fit to the residuals at the 99% confidence level, as the test statistics does not exceed the 99% critical value. For the normal distribution, we do reject the hypothesis of a good fit of the residuals. Based on these results we conclude that the Student-t provides a much better fit to the residuals of equation (3.12) than the normal distribution function.

Normal distribution	194.16 (24.73)
Student-t distribution	26.02 (26.22)

Chi-squared critical values for n-1 (number of intervals) at the 99% confidence level are in parentheses. Here n =12 for Normal distribution, and n=13 for Student-t distribution.[32] Reject the null-hypothesis that the Student-t is a good approximation for the noise term if the reported goodness-of-fit statistic exceeds the corresponding critical value.

Table 3.4: Goodness-of-fit-results for the residuals of equation (3.11)

3.4.4 Monte-Carlo simulation

The result from the previous section has important implications for risk management and derivatives valuation. For both applications it hold that many use the normal distribution function to generate random numbers from in Monte Carlo (MC) simulations. As we have seen in the previous section, this is an erroneous assumption. As these MC simulations are used to calculate portfolio Value at Risk type of risk statistics (discussed in Chapter 6), and to valuate options or forwards for which the underlying is the day-ahead power price, one will underestimate the probability of very small and extreme price changes, and will overestimate the probability of medium price changes. This is clearly visible after comparing the histograms and the distributional fits in the figures 3.2 and 3.3. In order to show the difference for MC simulations of day-ahead power prices, we show the outcomes of such a simulation in the following figure. We use equation (3.11) as our data-generating model. We simulate two series for the APX time series: one where the residuals are normally distributed and the other where the residuals are Student-t distributed. Here the number of degrees of freedom is set equal to 3.182. In both cases we assume the innovations to be IID and to have equal variance as indicated in table 3.2. We set the number of simulated observations equal to 933, being the number of APX prices that we have available. Figure 3.4 shows graphs of the simulated time series. As we expected, it can be easily observed that the Student-t simulated prices resemble more closely the true price path of power prices than the normal simulated prices.

[32] Boothe and Glassmann use 14 intervals (1987).

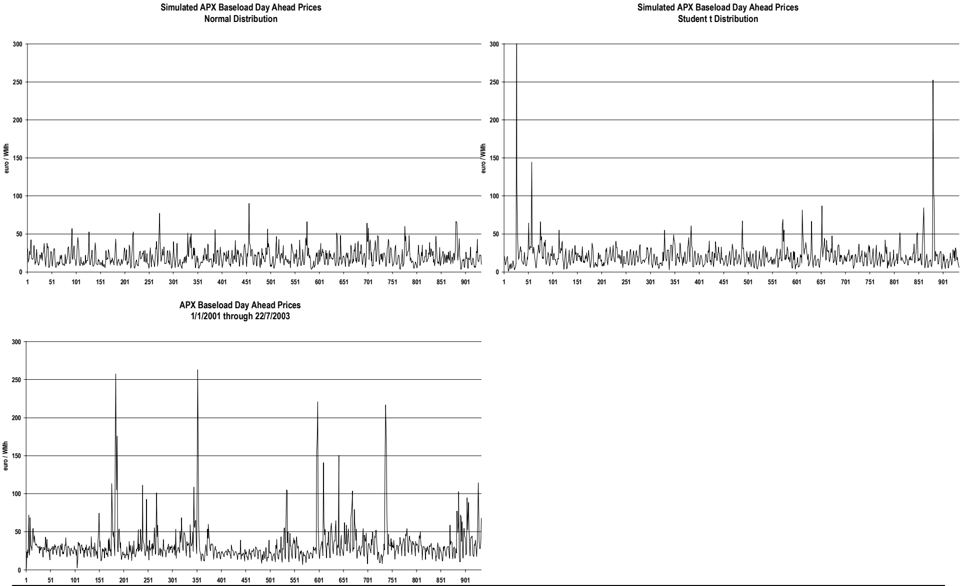

Figure 3.4: Simulated APX base load day-ahead prices based on equation (3.11) with normal innovations (top left), Student-t innovations (top right), and the actual APX prices (bottom left).

In table 3.5 we provide the descriptive statistics of the simulated APX base load day-ahead prices based on equation (3.11) with normal innovations and Student-t innovations, together with the statistics from the actual price series (see also table 3.1).

	Price level	Normal level	Student-t level
Mean	32.69	36.21	37.59
Median	26.92	35.02	34.97
Standard deviation	25.03	26.94	29.33
Skewness	4.675	1.339	2.682
Excess kurtosis	32.22	5.487	21.41

Table 3.5: Descriptive statistics of APX baseload prices based on equation (3.12) with normal innovations, Student t innovations, and the actual prices. Prices are in €/MWh.

From the mean and median estimates listed in table 3.5, we can see that around the center of the distribution both methods perform equally well.[33] For the higher-order moments

[33] The median is a robust estimator of the center of the distribution, as it is less sensitive to outliers than the mean.

(skewness and excess kurtosis) however, the Student-t method (2.682 and 21.41) more closely resembles the true price pattern (4.675 and 32.22) than the normal based method (1.339 and 5.487). Note that the kurtosis estimate of the Student-t simulate price path is still lower than the kurtosis estimate from the actual price series, which indicates that the probability of extreme price values to occur is higher in reality than is dictated from the Student-t simulated series. An important point worth emphasizing is that the two displayed simulated price paths presented above, are randomly chosen from 1000 MC simulations with normal innovations and 1000 MC simulations with Student-t innovations. The summary statistics of all simulations are given in Appendix A3.4. The results are fairly similar to the provided empirical evidence.

3.5 Concluding remarks

In this Chapter we demonstrate that assuming normal innovations in Monte Carlo simulations for risk management purposes can have serious consequences for the true amount of risk faced. We propose the Student-t distribution as an alternative to the normal distribution as it is capable of incorporating the fat tailed behaviour of electricity prices. We assess the amount of tail fatness of electricity price model residuals using extreme value theory and use its results directly to parameterise the Student-t. It is then shown that the Student-t provides a much better fit than the normal distribution. A fact that becomes especially clear when one observes the differences in simulation outcomes for the normal based method and the Student-t method. Therefore, the normality assumption that researchers and practitioners often make in their simulation or valuation method can lead to erroneous conclusions. The method that we proposed in this study is an easy to implement alternative for using the normal distribution as the density function for innovations in Monte Carlo simulations. In this method, spikes are captured through the selection of distribution function. We claim this method to be a candidate to model the non-normal behaviour of electricity prices in addition to other models such as jump diffusion models or switching regimes models.

3.6 Appendix

μ	3.482 (0.035)***	α	0.385 (0.048)***	SIC	0.665
β_1	-0.293 (0.031)***	σ	0.333	Jarque-Bera	1099.2
β_2	-0.644 (0.033)***	R^2	0.512	White	16.53

Newey-West standard errors are in parentheses. Significant at: ***99%, **95%, *90% confidence level. The estimate for μ of 3.482 relates to a long-term average price of €35.52 p/MWh. SIC (Schwartz Information Criterion). Number of observations: 933

Table A.3.1: NLS parameter estimates and residual characteristics for equation (3.11)

Seasonality

We include sinusoidal terms in equation 3.11, to take into account seasonality effects:

$$\Delta s(t) = \alpha\mu + \beta_1\{D_1(t)+(\alpha-1)\ D_1(t-1)\} + \beta_2\ \{D_2(t) + (\alpha-1)\ D_2(t-1)\}-\alpha s(t-1) \\ + \gamma\ \cos^*((2\pi t)/365) + \delta \sin((2\pi t)/365) + \theta\Delta s(t-7)\ \sigma\varepsilon(t),\ \varepsilon_t \sim IID \qquad (A.3.2)$$

The parameter estimates are given in table A3.3. We find weak evidence of seasonality. We select our model based on the Bayesian Information Criterion (SIC). Models with lower SIC values are usually preferred (Verbeek, 2004). Based on the lower SIC value of equation 3.11 (see table 3.2), we do not include a sinusoïdal term in our model.

μ	3.498 (0.032)***	γ	0.017 (0.016)	Adj. R^2	0.516
β_1	-0.303 (0.029)***	δ	-0.056 (0.032)*	SIC	0.625
β_2	-0.645 (0.029)***	θ	0.071 (0.032)**	Jarque-Bera	959.5
α	0.379 (0.026)***	σ	0.323	White	6.287

Newey-West standard errors are in parentheses. Significant at: ***99%, **95%, *90% confidence level. The estimate for μ of 3.479 relates to an long-term average price of 32.43 euro per MWh. Number of observations: 933

Table A3.3: NLS parameter estimates and residual characteristics for equation (3.11).

1000 MC simulations
The descriptive statistics obtained from the MC simulations of figure 3.4 (presented in table 3.5) should not be interpreted in isolation. Therefore we provide the summary statistics over *all* 1000 MC simulations with normal innovations. We do the same for the 1000 MC simulated series with a Student-t distributed noise term in our data-generating model. The statistics are given below.

	Summary statistics				
	Mean	Median	Std. dev	Skew	Ex. kurt.
Normal	37.82	34.05	30.02	1.497	6.739
Student-t	39.68	32.21	35.90	6.093	58.13
Actual	32.69	26.92	25.04	4.679	32.22

Table A3.4: Descriptive statistics of 1000 MC simulated APX baseload prices based on Equation (3.11) with normal innovations, Student t innovations. Prices are in €/MWh

When we compare the statistics from table A3.4 with the statistics listed in table 3.5, we can conclude that the results are similar except for the standard deviation (respectively 58.13 versus 21.14) and kurtosis estimate (respectively 35.90 versus 29.33) of the 1000 MC simulated Student-t price paths. This can be explained by the fact that in some of the 1000 Student-t simulated price paths, extreme positive values were generated relatively often, with maximum values up to €1100/MWh, that pushed the overall values of the mean, standard deviation estimates and excess kurtosis to this high level.

Chapter 4: Hourly electricity spot prices[34]

-Empirical study in international day-ahead markets-

4.1 Introduction

Since the worldwide structural reforms and market liberalization that started in the early 1990's, market places have been created, on which market participants can trade electricity forward contracts for different delivery periods. Typically, short-term contracts are traded on day-ahead markets that involve delivery of electricity in the next day and on intra-day markets that involve delivery in 15 or 30 minutes after the transaction (See Chapter 2 and 3). Note that the delivery periods of these markets are complementary.

In this Chapter, we focus on the hourly dynamics of electricity prices in day-ahead markets. Due to the non-storability of electricity, day-ahead prices exhibit specific characteristics such as mean-reversion, seasonality, spikes and a complex time-varying volatility structure. Many of these results were obtained from studying the time series of daily average prices (See also previous Chapter). An overview of the different models can be obtained from Bunn and Karakatsani (2003), Escribano et al. (2002), Huisman and Mahieu (2003), Lucia and Schwartz (2002) and Pilipovic (1998). The dynamics of daily prices are extremely important as these prices are used as reference point for marking to market valuations and serve as a base for option contracts such as callable options. However, the average prices mentioned above are indeed averages and do not meet the micro-structure of the day-ahead market itself.

The models developed for daily average prices cannot be directly applied to describe dynamics in hourly prices. For example, if hourly prices revert to an hourly specific mean level, then the daily average model with a daily mean will not suffice. Other questions are whether the level of mean-reversion is constant over the day or different per hour and whether the volatility structure is constant throughout the day. In addition, what is the correlation pattern between specific hours? These questions are relevant as many agents in the electricity markets are exposed to hourly variation. Power generation plants let their nomination depend on the expected prices for electricity delivery throughout the day. Companies that use electricity in a certain profile through the day that cannot be resembled by standard baseload and peakload contracts might have a demand for contracts that deliver only in a few hours of the day. To valuate these contracts market makers need to assess the expectations and risks for those specific hours and cannot rely on daily average prices only. Other applications can be found in power risk management, contract structuring and derivative pricing; E.g. hourly power options are currently traded in the US markets, and to a lesser extent in the European market[35].

A few studies have recognized the need for higher frequency modeling and have addressed some interesting issues. Borenstein et. al (2002) and Saravia (2004) find a spread between day-ahead and real-time hourly prices on the U.S. power markets, and attribute it to market power and speculation activity. Longstaff and Wang (2004) study the day-ahead hourly risk premium, calculated as the difference between the day-ahead price and the expected

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[34] This Chapter is based on: R. Huisman, C. Huurman and R. Mahieu (2006), "Hourly electricity prices in day-ahead markets" forthcoming in: *Energy Economics*. We thank participants at Energyforum conference in London (15-17 November 2005) for valuable comments.

[35] See Eydeland and Wolyniec (2003) for an overview on electricity option contracts.

real time price. They find that premiums are affected by demand, sales and price variation. Furthermore they study time variation in premiums by specifying a system of VAR's for each of the 24 hours in which ex-ante measures of risk (demand load and sales) are used as explanatory variables for unexpected price changes. Wolak (1997) studies the hourly price formation of the deregulated day-ahead electricity markets of England and Wales, Scandinavia, Australia and New Zealand. Wolak applies a Principal Component Analysis to the error covariance matrix obtained from a VAR hourly (or half hourly) price system to gain insight in the intra-day correlation of the errors terms. Wolak finds that the 'Anglo-Saxon' prices are difficult to forecast (i.e. 22 principal components explain 90% of variation in England and Wales data) compared to the NPX prices (5 principal components explain 90% of variation). Nogales et. al. (2002) use price- and demand load data obtained from the Spanish and U.S. market to forecast next-day electricity prices by time series models. Li and Flynn (2004) examine the hourly rate of price changes in 14 deregulated markets. Knittel and Roberts (2005) fit a range of traditional financial models and less conventional electricity price models to an hourly time series of real-time Californian electricity prices. They find that forecasting performance of traditional models is poor and can be substantially improved when they address the unique electricity price features are taken into account. Ramsay and Wang (1997) and Szkuta et. al (1999) do not rely on parametric modeling, and propose a neural network approach.
Some of these studies above, model each hour separately or assume some correlation pattern between the hours. Others stack the hourly prices and treat them as a time-series. An important difference between modeling daily average prices and modeling hourly prices is that hourly prices cannot be seen as a pure time series process. Time-series assume that the information set is updated by moving from one observation to the next in time. This assumption is not valid for hourly prices as the market microstructure does not allow for continuous trading. Many day-ahead markets are structured such that agents submit their bids and offers for delivery of electricity in all hours in the next day before a certain market closing time; hourly prices for next day delivery are determined at the same time. The information set used for setting the price of delivery in hour 23 is the same as the information set used to set the price for delivery in hour 5. Therefore, the information set is constant within the day and updates over the days. Applying directly a time-series approach is not sound from a methodological perspective and we propose a panel model to examine hourly price characteristics. A panel framework combines a time-dimension for the price movements from one day to the next, and a cross section dimension for the intra-day (hourly price) movements, which are set on the same moment in time!
This Chapter examines the dynamics in day-ahead hourly prices using a panel model. Data is obtained from the the APX (The Netherlands), EEX (Germany) and Powernext (hereafter PPX) from France. The empirical results show that hourly prices in day-ahead markets mean-revert around an hourly specific mean level, that the speed of mean-reversion is different over the hours (especially in super peak hours) and that a block structured cross-sectional correlation pattern is apparent. We extend the existing energy economics literature by disclosing that electricity prices revert back to an hourly mean level with varying mean-reversion rates, and we find evidence of a block structured cross-sectional correlation pattern between the hours. From the discussion above we conclude this has not been done before; i.e. Wolak (1997) does not take into account hourly varying means, nor focuses on the cross-sectional correlation pattern between the hours, and most

importantly proposes a VAR framework that not by definition matches the market microstructure to the extent that our panel framework does.

This Chapter is structured as follows. Section 4.2 sets out the panel methodology and focuses on the observed characteristics of hourly electricity prices. Section 4.3 provides an overview of our dataset. Section 4.4 discusses the empirical results. Section 4.5 concludes.

4.2 Panel methodology

In financial literature, panel models have been applied to exchange rates for instance. Each day, news affects the prices in the FX market and has a simultaneous impact on different exchange rates. For instance, news about the U.S. economy is likely to affect exchange rates that are denoted in terms of the U.S. Dollar. Therefore, the cross-section of U.S Dollar denoted exchange rates behave over time and their quotes respond to the same news factors (but perhaps to a different extent)[36]. To model hourly prices, observe that hourly prices can be seen as cross-sectional individuals (as their prices are quoted on the same time) whose price change over the day. Therefore, the panel framework exactly matches the micro-structure of day-ahead markets. We will now propose a general hourly price model, and three restricted versions of it. The set-up of these models is in the panel literature referred to as a fixed time-effects model[37].

4.2.1 General model

As discussed above, hourly electricity prices in day-ahead markets do not follow a time-series process but are in fact a panel of 24 cross-sectional hours that vary from day to day. This is because the market microstructure of many day-ahead markets are quoted at the same moment on a day. For instance, the Dutch APX requires that bids and offers for each hour in the next day to be submitted before 11 a.m., and that these prices are published around noon. A trader uses exactly the same information to set the price for hour h as she uses to set the price for hour s (h being different from s). Proceeding to the next day, the information set updates, but it updates simultaneously for hour 1 through hour 24. Therefore, hourly prices within a day behave cross-sectionally and hourly dynamics over days behave according to time-series properties. To introduce the model, let $s_h(t)$ be the natural logarithm of the day-ahead price observed on day t for the delivery of one MW electricity in hour h of the following day t+1. Following Lucia and Schwartz (2002) and Huisman and Mahieu (2003), the day-ahead price is the sum of two independent components: a deterministic $f_h(t)$ and a stochastic component $x_h(t)$:

$$s_h(t) = f_h(t) + x_h(t) \tag{4.1}$$

The deterministic component $f_h(t)$ accounts for predictable regularities, such as mean price levels and other periodic behaviour. The deterministic consists of a mean price level μ_0 and and hourly deviations from mean price level to allow for differences in mean price levels over the hours, μ_h.for h = 1….23 (μ_{24} equals 0 to prevent from multicollinearity). The deterministic component also allows for different price levels for different weekdays of the

[36] See Huisman et al. (1998) for an application of a panel data model to describe the dynamics of change in exchange rates.
[37] Baltagi (1995) provides an overview of different panel model applications in economics.

week. To model this, $I^d(t)$ is a dummy that equals 1 if the delivery day t+1 is weekday d (d = 1 corresponds with a Saturday, d =2 corresponds with a Sunday, ….d = 7 corresponds with a Friday), and let β_d be the difference from the mean price level (β_7 equals zero to prevent from multicollinearity). The expression for the deterministic component therefore becomes:

$$f_h(t) = \mu_0 + \mu_h + \Sigma_d \beta_d I^d(t) \tag{4.2}$$

The stochastic component in equation 4.1 accounts for the variation of the hourly day-ahead price around the deterministic component. The stochastic part may account for characteristics that electricity prices exhibit such as mean-reversion, time-varying volatility and spikes. In this study, the stochastic component is a mean-reverting process. To model this, let α_h be the rate of mean-reversion for hour h; it reflects the speed with which the price moves back to its hourly fundamental component when the price deviated from that value yesterday. The expression for the stochastic component becomes:

$$x_h(t) = -\alpha_h x_h(t-1) + \varepsilon_h(t) \tag{4.3}$$

In equation (4.3), $\varepsilon_h(t)$ is the error term. The equations (4.2) and (4.3) disclose the combination of cross-sectional variation and time-series dynamics in the panel framework. The price for delivery in hour h of day t depends on the price for that hour on the previous day and not on the price in the previous hour.
The error term in equation (4.3), $\varepsilon_h(t)$, is assumed to be independent over the days but it allows for cross-sectional covariance between the hours. Allowing for cross-sectional correlation is important, as when a trader submits her quote delivery in hour h in the next day, she will let this quote depend on the information she has for all other hours observed at the time of quotation. Let $\varepsilon_h(t)$ be the (24 x 1) vector containing the hourly error term $\varepsilon_h(t)$ in row h and let Σ be the (24 x 24) hourly cross sectional covariance matrix that describes the dependence between hours in the same day (h = 1 through 24):

$$\varepsilon(t) \sim IID(0, \Sigma). \tag{4.4}$$

Equation (4.4) shows that one can disentangle cross-sectional dependence from time-series dependence. The covariance matrix Σ can be specified. In this study, the covariance matrix is not specified in order to examine the cross-sectional patterns that are embedded in the prices. The parameters in the model are estimated using the seemingly unrelated (SUR) method. SUR estimates the parameters of the 24 hourly time series, accounting for heteroskedasticity and contemporaneous correlations in the errors across the time series. We refer to Baltagi (1995) for an overview of panel models and their applications and for details on SUR.

4.2.2 Restricted models

We restrict the general model described in section 4.2.1, in three ways. We namely want to gain insight whether hourly price dynamics can be best described by a panel model that accounts for hourly varying mean-reversion rates only (i), hourly varying mean price levels only (ii), or neither of these characteristics (iii). An important point worth emphasizing is that the restricted models are nested in the general model.
(i) Let us first impose a restriction on the deterministic component described in equation (4.2) by assuming that μ_h equals zero. Then equation (4.2) becomes:

$$f_h(t) = \mu_0 + \Sigma_d \beta_d I^d(t) \qquad (4.5)$$

This restriction implies that we do not allow for differences in mean price levels over the hours. Observe that the deterministic component (4.5) still allows for different price levels for different days of the week. The stochastic component remains unchanged from the general model. Hence, the deterministic component and stochastic component of the restricted model (i) are respectively given by (4.3) and (4.5). We use SUR to estimate the parameters of the model.

(ii) We now leave the deterministic component in the general model unchanged. We impose a restriction on the stochastic component described in equation (4.3.) We assume that prices moves back with a daily constant rate α_0 to its hourly price mean level described in equation (4.2). Then (4.3) can be rewritten as:

$$x_h(t) = -\alpha_0 (t-1) + \varepsilon_h(t) \qquad (4.6)$$

The deterministic component and stochastic component of the restricted model (ii) are respectively given by (4.2) and (4.6). The error term in equation (4.6)), $\varepsilon_h(t)$, is given by equation (4.4). We use SUR to estimate the parameters of the model. In this model the deterministic component allows for different price levels for different weekdays of the weeks and hours of the day, but prices move back to the hourly mean price level with a constant speed, reflected by α_0.

(iii) This restricted model combined the aforementioned restrictions on the deterministic and stochastic component. We now assume that the price on hour h of day t is given by the sum of equation (4.5) and equation (4.6). The error term in equation (4.6) is given by equation (4.4). We perform SUR to obtain estimates for the parameters in equations (4.5) and (4.6). Although we only seem to exploit the time-series dimension of the panel, it is worth emphasizing that this is not true. We still allow for cross-sectional covariance between the hours through modeling the error covariance matrix Σ of (4.4). As mentioned earlier, this is important since a trader can let her quote for hour h on the next day depend on the information that she has for all other hours observed at the time of quotation.

4.2.3 Model specification tests

To formally test whether the general model is a better model specification than the restricted versions we employ a likelihood ratio test. This test compares the log-likelihood (LL) values of two nested models. The likelihood ratio (LR) test statistic is computed as:

$$LR = 2*(LLgeneral - LLrestricted) \qquad (4.7)$$

The LR test statistic is Chi-square distributed under the null-hypothesis of correctly imposed restrictions. The number of degrees of freedom is set equal to the number of exclusion restrictions (Verbeek, 2004).

4.3 Sample and data description

We use day-ahead prices from the year 2004 for three day-ahead markets: the Amsterdam Power Exchange (APX), the European Energy Exchange (EEX; Germany) and Powernext (PPX; France). The APX is the first electronic power-trading platform that is established in continental Europe for day-ahead trades. The EEX is a result of a merger in mid-year 2002, between the Leipzig Power Exchange (founded in August 2000) and the European Energy

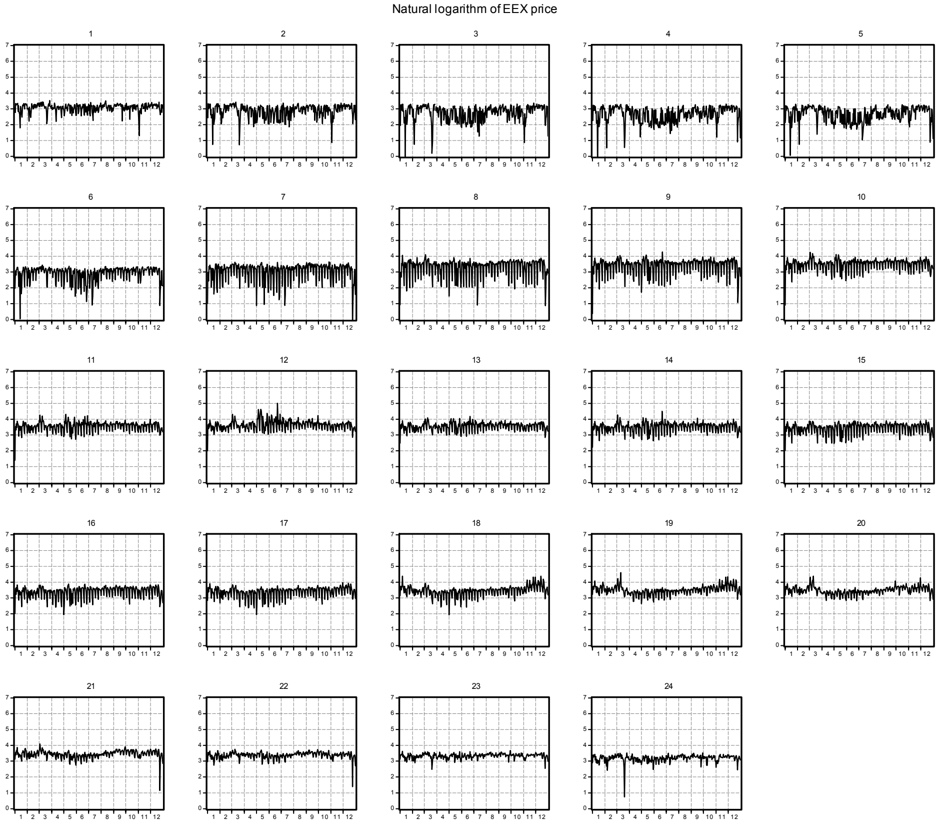
Exchange of Frankfurt. Since then the EEX has developed as the second most liquid (after the Scandinavian Nordic Power Exchange) market in Europe. The day-ahead power market of Powernext has been established in the end of 2001. These three markets have the same day-ahead market structure on hourly power contracts in common. Traders on the APX, EEX and PPX markets are required to submit all their bids and offers before respectively 11:00am, 12:00am and 11:00am for the next day delivery. Market prices are published around noon. For each market, we have 8784 observations (24 hours times 366 days). Table 4.1 provides an overview of descriptive statistics of this data in price levels and log prices.

	APX		EEX		PPX	
	Price	Log price	Price	Log price	Price	Log price
Mean	31.58	3.315	28.52	3.261	28.13	3.251
Median	28.70	3.357	28.17	3.338	28.01	3.333
Std deviation	22.26	0.563	10.80	0.470	10.41	0.459
Minimum	0.010	-4.605	0.450	-0.799	0.000	-3.219
Maximum	800.0	6.685	150.0	5.010	100.0	4.605
Skewness	10.46	-2.717	0.502	-1.609	0.210	-1.834
Exc. kurtosis	239.1	36.10	6.236	8.022	13.90	3.567

(8784 observations for each market).

Table 4.1: Descriptive statistics of APX-, EEX-, and PPX day-ahead prices for 2004.
Source: www.apx.nl (APX), www.eex.de (EEX) and www.powernext.fr (PPX)

Table 4.1 discloses the non-normal characteristics of the data being the positive skewness and excess kurtosis. From figure 4.1, we observe some well-documented stylized facts of power prices. We observe high volatility that seems to cluster over the days but not between hours. Compare for example the graphs of hour 19 and hour 20 in the month of March.



The top left graph represents the time-series of log day-ahead prices for hour 1.
The bottom right graph represents the time-series of log day-ahead prices for hour 24.

Figure 4.1: Natural logarithm of day-ahead prices for EEX market in 2004.

All hours clearly exhibit mean reversion that moves price back to a certain price level when a price shock has occurred. Furthermore we can clearly see that volatility patterns differ over the hours and the occurrence of positive and negative spikes. Note that negative spikes predominantly occur during night hours. This can be explained by the relatively high competition on the supply-side during these off-peak hours, when electricity is offered at discount prices in order to avoid costs for ramping down and ramping up later (Bunn and Karakatsani, 2003). We observe similar price patterns on the APX and PPX.

4.4 Results

We now present and discuss the empirical results obtained from the general hourly price model (section 4.4.1) and the restricted versions of the model (section 4.4.2.).

4.4.1. Results general model

The tables 4.2 (APX), 4.3 (EEX) and 4.4 (PPX) contain the SUR estimates for the parameters in equations 4.2, 4.3 and 4.4.

μ_0	3.290 (0.020)***	μ_{19}	0.340 (0.026)***	α_{15}	0.770 (0.024)***
μ_1	-0.134 (0.011)***	μ_{20}	0.283 (0.020)***	α_{16}	0.771(0.024)***
μ_2	-0.342 (0.017)***	μ_{21}	0.221 (0.016)***	α_{17}	0.650 (0.029)***
μ_3	-0.471(0.020)***	μ_{22}	0.144 (0.010)***	α_{18}	0.441 (0.029)***
μ_4	-0.572 (0.024)***	μ_{23}	0.100 (0.009)***	α_{19}	0.446 (0.028)***
μ_5	-0.573 (0.023)***	α_1	0.787 (0.025)***	α_{20}	0.487 (0.026)***
μ_6	-0.410 (0.033)***	α_2	0.778 (0.024)***	α_{21}	0.509 (0.028)***
μ_7	-0.288 (0.045)***	α_3	0.745 (0.023)***	α_{22}	0.633 (0.028)***
μ_8	-0.054 (0.051)	α_4	0.820 (0.027)***	α_{23}	0.818 (0.031)***
μ_9	0.189 (0.029)***	α_5	0.781 (0.023)***	α_{24}	0.742 (0.028)***
μ_{10}	0.368 (0.024)***	α_6	0.854 (0.034)***	β_1	-0.171(0.020)***
μ_{11}	0.458 (0.024)***	α_7	0.941 (0.028)***	β_2	-0.359 0.023)***
μ_{12}	0.530 (0.025)***	α_8	0.931 (0.028)***	β_3	0.031 (0.024)***
μ_{13}	0.382 (0.017)***	α_9	0.869 (0.023)***	β_4	0.084 (0.023)***
μ_{14}	0.367 (0.020)***	α_{10}	0.832 (0.025)***	β_5	0.063 (0.023)***
μ_{15}	0.283 (0.020)***	α_{11}	0.770 (0.024)***	β_6	0.062 (0.020)***
μ_{16}	0.220 (0.020)***	α_{12}	0.703 (0.026)***	Adj.R^2	0.941
μ_{17}	0.208 (0.023)***	α_{13}	0.766 (0.026)***	Durbin Watson	2.060
μ_{18}	0.428 (0.049)***	α_{14}	0.811 (0.023)***	Log-LH	-8645.5

Standard errors are in parentheses. Significant at: ***99%, **95%, *90% confidence level. Number of observations: 8784

Table 4.2: SUR parameter estimates for the general model for APX prices

We first focus on the estimates for the deterministic component in equation 4.2. In the tables, β_1 represents a Saturday, β_2 stands for a Sunday, β_3 is a Monday and so forth. Both β_1 and β_2 are negative for all markets indicating the lower prices for electricity delivered on weekend days. The β parameters are all significant and are in line with results from

μ_0	3.236(0.020)***	μ_{19}	0.321 (0.016)***	α_{15}	0.776 (0.018)***
μ_1	-0.111 (0.016)***	μ_{20}	0.293 (0.014)***	α_{16}	0.774 (0.018)***
μ_2	-0.316 (0.021)***	μ_{21}	0.264 (0.014)***	α_{17}	0.721 (0.020)***
μ_3	-0.448 (0.027)***	μ_{22}	0.196 (0.012)***	α_{18}	0.601 (0.022)***
μ_4	-0.535 (0.029)***	μ_{23}	0.153 (0.008)***	α_{19}	0.541 (0.022)***
μ_5	-0.501 (0.027)***	α_1	0.832 (0.030)***	α_{20}	0.536 (0.023)***
μ_6	-0.267 (0.025)***	α_2	0.811 (0.026)***	α_{21}	0.599 (0.023)***
μ_7	-0.132 (0.030)***	α_3	0.757 (0.025)***	α_{22}	0.651 (0.022)***
μ_8	0.118 (0.029)***	α_4	0.744 (0.024)***	α_{23}	0.712 (0.025)***
μ_9	0.231 (0.026)***	α_5	0.708 (0.025)***	α_{24}	0.787 (0.031)***
μ_{10}	0.326 (0.018)***	α_6	0.784 (0.028)***	β_1	-0.209 (0.019)***
μ_{11}	0.384 (0.016)***	α_7	0.830 (0.023)***	β_2	-0.356 (0.022)***
μ_{12}	0.469 (0.018)***	α_8	0.867 (0.023)***	β_3	-0.001 (0.022)***
μ_{13}	0.378 (0.015)***	α_9	0.841 (0.021)***	β_4	0.039 (0.022)***
μ_{14}	0.337 (0.017)***	α_{10}	0.829 (0.018)***	β_5	0.038 (0.021)***
μ_{15}	0.269 (0.018)***	α_{11}	0.814 (0.018)***	β_6	0.069 (0.019)***
μ_{16}	0.219 (0.018)***	α_{12}	0.693 (0.024)***	Adj.R^2	0.955
μ_{17}	0.208 (0.018)***	α_{13}	0.741 (0.020)***	Durbin Watson	2.052
μ_{18}	0.274 (0.018)***	α_{14}	0.805 (0.021)***	Log-LH	-8331.0

Standard errors are in parentheses. Significant at: ***99%, **95%, *90% confidence level. Number of observations: 8784

Table 4.3: SUR parameter estimates for the general model for EEX prices

Huisman and Mahieu (2003) among others. The average mean log price level μ_0 vary between 3.236 (€25.43) for the EEX and 3.300 (€27.11) for the PPX. The values for μ_1 through μ_{23} reflect the hourly deviation from the mean price level. The estimates for μ_h are negative for hours 1 through 7 indicating the lower prices for off-peak delivery of power. Prices then increase for later hours and decrease late in the evening. These estimates make sense as demand for power is low in weekend and off-peak hours on weekdays and high in peak hours. The estimates for the mean-reversion parameters α_h in the stochastic component in equation (4.3) show some differences over the hours.

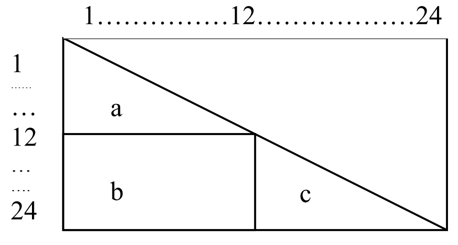
μ_0	3.300 (0.020)***	μ_{19}	0.274 (0.016)***	α_{15}	0.753 (0.020)***
μ_1	-0.196 (0.015)***	μ_{20}	0.263 (0.013)***	α_{16}	0.804 (0.022)***
μ_2	-0.322 (0.019)***	μ_{21}	0.187 (0.010)***	α_{17}	0.758 (0.025)***
μ_3	-0.429 (0.021)***	μ_{22}	0.134 (0.009)***	α_{18}	0.614 (0.022)***
μ_4	-0.566 (0.023)***	μ_{23}	0.096 (0.006)***	α_{19}	0.479 (0.021)***
μ_5	-0.684 (0.033)***	α_1	0.779 (0.027)***	α_{20}	0.436 (0.020)***
μ_6	-0.404 (0.023)***	α_2	0.761 (0.024)***	α_{21}	0.546 (0.020)***
μ_7	-0.241 (0.034)***	α_3	0.699 (0.023)***	α_{22}	0.600 (0.022)***
μ_8	0.011 (0.027)***	α_4	0.659 (0.024)***	α_{23}	0.641 (0.022)***
μ_9	0.169 (0.024)***	α_5	0.666 (0.025)***	α_{24}	0.715 (0.023)***
μ_{10}	0.265 (0.017)***	α_6	0.773 (0.027)***	β_1	-0.226 (0.020)***
μ_{11}	0.312 (0.015)***	α_7	0.808 (0.029)***	β_2	-0.403 (0.024)***
μ_{12}	0.364 (0.0315)***	α_8	0.790 (0.023)***	β_3	-0.048 (0.025)***
μ_{13}	0.319 (0.013)***	α_9	0.865 (0.021)***	β_4	0.051 (0.024)***
μ_{14}	0.282 (0.013)***	α_{10}	0.800 (0.019)***	β_5	0.046 (0.023)***
μ_{15}	0.223 (0.014)***	α_{11}	0.773 (0.020)***	β_6	0.045 (0.020)***
μ_{16}	0.170 (0.016)***	α_{12}	0.700 (0.022)***	Adj.R^2	0.942
μ_{17}	0.154 (0.018)***	α_{13}	0.702 (0.021)***	Durbin Watson	2.065
μ_{18}	0.216 (0.016)***	α_{14}	0.749 (0.019)***	Log-LH	-8239.5

Standard errors are in parentheses. Significant at: ***99%, **95%, *90% confidence level. Number of observations: 8784

Table 4.4: SUR parameter estimates for the general model for PPX prices

The estimates are in the range of 0.65 and 0.95 until hour 17 and then fall to values in the range of 0.40 and 0.65 for the hours 18 through 22. Clearly, mean-reversion is not stable over the day; super-peak hours (18 through 22) exhibit significant less mean-reversion. This can be explained by the higher demand for power in these hours resulting in less reserve production capacity and therefore an increased probability of shortages and spikes. Prices in these hours are less predictable. This result is important. Forward and options contracts in super peak hours should not be valuated based on models that use data for baseload and/or peakload forward contracts as those prices will overestimate the true amount of mean-reversion. In nomination schemes, one should be careful assuming any price dependencies in the super peak hours. As discussed in section 4.1, studying the time series of daily average prices has been done extensively in energy economics literature. Huisman and Mahieu (2003) observe mean-reversion estimates for the APX of approximately 0.37 (for the years 2001 and 2002). Our result indicates that mean-reversion is not constant throughout the day. The level of mean-reversion is significantly lower in the super peak hours. From the tables 4.2, 4.3 and 4.4, we see that the Durbin-Watson test statistics are all around 2, which implies that the hourly APX, EEX and PPX price series exhibit no serial correlation. We note that the autocorrelation correlograms (not reported) indicate that there is a small level of autocorrelation at certain daily time lags.[38] A point worth emphasizing is that the adjusted R^2 can be subject to spurious interpretation, since this criterion is only appropriate for evaluating the model's fit for OLS estimations. We will therefore rely on the log-likelihood figures reported in the tables (noted as Log-LH), when we examine and compare the fit of the different models used in this study.

Other interesting observations on hourly stochastic patterns show up in the (24 x 24) estimates cross-sectional correlation matrix. For the EEX the estimates are listed in table 4.5a, 4.5b and 4.5c. Since the format of this booklet does not allow us to display the matrix as a whole, we cut the matrix in three parts, noted as a, b and c as is shown in textbox 4.1. Let's use the notation m and n for respectively the rows and columns of the (24h x 24h) cross-sectional error correlation matrix Here part a are the elements (m,n), where m= 1 to 12, and n = 1 to 12. Part b are the elements (m,n), where m= 1 to 12, and n = 13 to 24. And Part c are the elements (m,n), where m= 13 to 24, and n = 13 to 24



The dimensions of the (m x n) correlation matrix are 24h x 24h, as can be seen from the x-axis and y-axis.

Textbox 4.1 Display scheme of the elements of the cross-sectional error correlation matrix shown in table 4.5a, 4.5b and 4.5c.

The estimated cross-sectional correlation matrix of the other markets are shown in the Appendix (A4.1-A4.6).

[38] Autocorrelation is apparent at lag 1 and 7 in all three datasets, which could be partly successfully removed (only for lag 7 through inclusion of AR (7) term). We note that the Durbin-Watson test for fixed effects panel data models, as specified by Bhargava et al. (1982) who provide theoretical guidance on the Durbin-Watson tests in panel data model), is not feasible since the upper and lower bounds for the Durbin-Watson test statistics are not known for a large T (in our panel T =365).

In the tables 4.5 (a, b and c), the correlation numbers bigger than 0.5 are reported boldfaced; non-significant correlations are left blank[39]. The tables 4.5 (a,b and c) show evidence for a clear cross-sectional correlation structure in hourly electricity prices.

Firstly, observe the high correlations ranging between 0.732 (between hour 20 and 21) and 0.964 (between hour 15 and 16) between two adjacent hours. An explanation for this effect is that consumption and capacity flows over the hours; if reserve capacity is low in one hour it will probably be low in the next hour as well and if demand is high in one hour it will probably be high in the next hour as well. Secondly, observe the block-structure of correlations. The first block is identified by the hours 1 to 6 (table 4.5a) and hour 24 (table 4.5.c). Prices in these off-peak hours exhibit high cross-sectional correlations. The second block shows up in the peak hours from hour 6 through hour 19. Again prices in these hours are highly correlated. There is evidence for a clear peak off-peak correlation structure but, interestingly, the boundaries of the peak block do not perfectly match the market definition of peak hours[40]. A possible explanation for the relatively low correlation between peak hours and off-peak hours is that the difference in reserve capacity between the two blocks. The lower reserve capacity in the peak hours implies that the prices in those hours are more volatile and exhibit more spikes than prices in off-peak hours.
The empirical results from the general panel model show that hourly prices in day-ahead markets mean-revert around an hourly specific mean price level, that the speed of mean-reversion is different over the hours (especially in super-peak hours) and that a block-structured cross-sectional correlation pattern is apparent.

4.4.2. Results restricted models

We now will present and discuss the results for the restricted models (i), (ii) and (iii).
in equations 4.2, 4.3 and 4.4. The estimation results for the cross-sectional correlation matrices of the error term are not shown here, but show similar patterns to those reported for the general model (see table 3.5 and the Appendix A4.1 – A4.6).

Restricted model (i)

The tables 4.6 (APX), 4.7 (EEX) and 4.8 (PPX) contain the SUR estimates for the parameters in equations (4.3) and (4.5).

[39] The Fisher-transformation is a common way to test whether the correlation coefficient is significantly different from zero. The correlation coefficient r is transformed as: z =√(ln 1+ r / 1-r). Here z is approximately normally distributed with standard error 1 / √(N-3), where N is the sample size. We use a 99% confidence interval (critical value is 2.575).

[40] Note that the definition of peak hours differs per market: At the EEX and Powernext peak hours are from 8.00 am to 20.00 pm. At the APX peak hours are from 7.00am to 23.00 pm.

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1	1.000											
2	**0.854**	1.000										
3	**0.777**	**0.909**	1.000									
4	**0.729**	**0.840**	**0.929**	1.000								
5	**0.633**	**0.747**	**0.805**	**0.894**	1.000							
6	0.361	**0.548**	**0.595**	**0.645**	**0.744**	1.000						
7	0.039	0.255	0.311	0.347	0.453	**0.744**	1.000					
8	-.029	0.196	0.221	0.210	0.308	**0.609**	**0.886**	1.000				
9		0.217	0.248	0.234	0.297	**0.564**	**0.815**	**0.908**	1.000			
10	0.152	0.302	0.319	0.326	0.382	**0.585**	**0.757**	**0.790**	**0.885**	1.000		
11	0.184	0.288	0.303	0.327	0.384	**0.514**	**0.664**	**0.647**	**0.753**	**0.906**	1.000	
12	0.102	0.153	0.164	0.197	0.269	0.378	0.496	0.442	**0.537**	**0.701**	**0.864**	1.000

Here we report only those elements that are significantly different from zero at a 99% confidence interval by employing a Fisher-test. The correlation numbers bigger than 0.5 are reported boldfaced; non-significant correlations are left blank.

Table 4.5a. Part (see textbox 3.1) of cross-sectional correlation matrix for the EEX market

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
13	0.199	0.268	0.282	0.322	0.381	0.479	**0.588**	**0.529**	**0.630**	**0.810**	**0.924**	**0.883**
14	0.087	0.200	0.230	0.254	0.313	0.493	**0.662**	**0.645**	**0.738**	**0.854**	**0.891**	**0.786**
15	0.054	0.199	0.241	0.248	0.313	**0.535**	**0.749**	**0.740**	**0.811**	**0.876**	**0.844**	**0.697**
16	0.036	0.204	0.256	0.271	0.335	**0.554**	**0.776**	**0.767**	**0.831**	**0.852**	**0.804**	**0.641**
17	0.066	0.237	0.276	0.285	0.346	**0.508**	**0.679**	**0.700**	**0.745**	**0.787**	**0.743**	**0.552**
18	0.086	0.201	0.244	0.296	0.346	0.432	**0.511**	0.493	**0.512**	**0.600**	**0.598**	0.448
19	0.167	0.234	0.280	0.367	0.415	0.392	0.345	0.272	0.294	0.435	0.489	0.379
20	0.285	0.298	0.330	0.411	0.446	0.354	0.232	0.112	0.141	0.332	0.414	0.352
21	0.293	0.277	0.329	0.444	0.492	0.424	0.366	0.124	0.116	0.319	0.395	0.393
22	0.363	0.322	0.354	0.443	0.477	0.374	0.296	0.032	0.035	0.241	0.358	0.407
23	**0.509**	0.422	0.397	0.448	0.434	0.204		-.175	-.149	0.068	0.224	0.293
24	**0.524**	**0.544**	**0.536**	**0.538**	0.494	0.313	0.146			0.179	0.257	0.232

Here we report only those elements that are significantly different from zero at a 99% confidence interval by employing a Fisher-test. The correlation numbers bigger than 0.5 are reported boldfaced; non-significant correlations are left blank.

Table 4.5b. Part (see textbox 3.1) of cross-sectional correlation matrix for the EEX market

	13	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
13	1.000											
14	**0.906**	1.000										
15	**0.832**	**0.922**	1.000									
16	**0.778**	**0.880**	**0.964**	1.000								
17	**0.707**	**0.813**	**0.900**	**0.936**	1.000							
18	**0.603**	**0.672**	**0.736**	**0.768**	**0.864**	1.000						
19	**0.535**	**0.526**	**0.539**	**0.547**	**0.640**	**0.839**	1.000					
20	0.487	0.419	0.408	0.392	0.460	**0.632**	**0.875**	1.000				
21	**0.504**	0.405	0.392	0.389	0.357	0.464	**0.609**	**0.732**	1.000			
22	0.485	0.346	0.317	0.304	0.246	0.341	**0.505**	**0.661**	**0.921**	1.000		
23	0.355	0.183	0.128	0.109	0.118	0.259	0.456	**0.623**	**0.701**	**0.817**	1.000	
24	0.347	0.247	0.220	0.220	0.252	0.319	0.435	**0.532**	**0.566**	**0.645**	**0.819**	1.000

Here we report only those elements that are significantly different from zero at a 99% confidence interval by employing a Fisher-test. The correlation numbers bigger than 0.5 are reported boldfaced; non-significant correlations are left blank.

Table 4.5c. Part (see textbox 3.1) of cross-sectional correlation matrix for the EEX market

μ_0	3.306 (0.018)***	α_{12}	0.415 (0.019)***	α_{24}	0.659 (0.029)***
α_1	0.693 (0.026)***	α_{13}	0.393 (0.019)***	β_1	-0.152 (0.020)***
α_2	0.564 (0.021)***	α_{14}	0.540 (0.020)***	β_2	-0.345 (0.023)***
α_3	0.496 (0.019)***	α_{15}	0.545 (0.021)***	β_3	0.065 (0.024)***
α_4	0.561 (0.022)***	α_{16}	0.597 (0.023)***	β_4	0.070 (0.024)***
α_5	0.486 (0.019)***	α_{17}	0.553 (0.026)***	β_5	0.056 (0.023)***
α_6	0.694 (0.031)***	α_{18}	0.359 (0.025)***	β_6	0.049 (0.020)***
α_7	0.831 (0.028)***	α_{19}	0.295 (0.023)***	Adj.R^2	0.935
α_8	0.848 (0.029)***	α_{20}	0.329 (0.022)***	Durbin Watson	2.196
α_9	0.696 (0.025)***	α_{21}	0.305 (0.024)***	Log-LH	-8713.7
α_{10}	0.587 (0.023)***	α_{22}	0.426 (0.025)***		
α_{11}	0.502 (0.020)***	α_{23}	0.666 (0.030)***		

Standard errors are in parentheses. Significant at: ***99%, **95%, *90% confidence level. Number of observations: 8784

Table 4.6: SUR parameter estimates for the restricted model (i) for APX prices

μ_0	3.411 (0.017)***	α_{12}	0.428 (0.019)***	α_{24}	0.600 (0.026)***
α_1	0.644 (0.028)***	α_{13}	0.464 (0.017)***	β_1	-0.199 (0.019)***
α_2	0.602 (0.022)***	α_{14}	0.617 (0.020)***	β_2	-0.347 (0.022)***
α_3	0.566 (0.022)***	α_{15}	0.665 (0.018)***	β_3	-0.001 (0.023)***
α_4	0.505 (0.020)***	α_{16}	0.696 (0.018)***	β_4	0.041 (0.023)***
α_5	0.424 (0.019)***	α_{17}	0.649 (0.020)***	β_5	0.038 (1.743)***
α_6	0.553 (0.024)***	α_{18}	0.514 (0.020)***	β_6	0.064 (0.019)***
α_7	0.606 (0.023)***	α_{19}	0.422 (0.020)***	Adj.R^2	0.945
α_8	0.766 (0.023)***	α_{20}	0.432 (0.021)***	Durbin Watson	2.162
α_9	0.753 (0.021)***	α_{21}	0.465 (0.022)***	Log-LH	-8375.9
α_{10}	0.657 (0.019)***	α_{22}	0.554 (0.023)***		
α_{11}	0.557 (0.018)***	α_{23}	0.605 (0.026)***		

Standard errors are in parentheses. Significant at: ***99%, **95%, *90% confidence level. Number of observations: 8784

Table 4.7: SUR parameter estimates for the restricted model (i) for EEX prices

μ_0	3.385 (0.019)***	α_{12}	0.471 (0.018)	α_{24}	0.528 (0.024)
α_1	0.600 (0.025)***	α_{13}	0.468 (0.017)	β_1	-0.021 (0.019)
α_2	0.559 (0.022)***	α_{14}	0.571 (0.017)	β_2	-0.389 (0.023)
α_3	0.449 (0.019)***	α_{15}	0.660 (0.019)	β_3	-0.041 (0.025)
α_4	0.378 (0.016)***	α_{16}	0.728 (0.022)	β_4	0.070 (0.024)
α_5	0.411 (0.019)***	α_{17}	0.701 (0.025)	β_5	0.063 (0.023)
α_6	0.649 (0.021)***	α_{18}	0.520 (0.021)	β_6	0.052 (0.019)
α_7	0.661 (0.025)***	α_{19}	0.386 (0.018)	Adj.R^2	0.933
α_8	0.757 (0.022)***	α_{20}	0.340 (0.017)	Durbin Watson	2.191
α_9	0.650 (0.031)***	α_{21}	0.427 (0.019)	Log-LH	-8249.4
α_{10}	0.650 (0.019)***	α_{22}	0.475 (0.022)		
α_{11}	0.556 (0.018)***	α_{23}	0.511 (0.022)		

Standard errors are in parentheses. Significant at: ***99%, **95%, *90% confidence level. Number of observations: 8784

Table 4.8: SUR parameter estimates for the restricted model (i) for PPX prices

The estimates presented in the tables 4.6, 4.7 and 4.8 correspond with the restricted model (i). This model allows for hourly-varying mean reversion rates. In contrast to the general framework we have restricted the hourly-varying mean price level, such that $\mu_h=0$ (h=1….24). Hence, an important difference between the general model and this restricted version is that hourly prices revert back to a constant mean price level throughout the day.
When we compare the estimates for the mean-reversion parameters α_h of the general model with the restricted version (i) we observe the following difference: the α_h estimates of the restricted model are overall in a lower range, which can be explained by the fact that prices revert back to a constant mean-price level throughout the day. Ignoring the price characteristic of power prices that mean price levels vary between hours, leads to underestimation of the true mean-reversion levels. An important point worth emphasizing when we examine the mean-reversion parameters of the restricted model in light of the μ_h estimates reported for the general model, is that the highest values of α_h are reached in the hours (hours 6 to 9, and hours 16 and 17), when the change in value between the μ_h estimate on hour h, and the estimate μ_{h+1} on the adjacent hour h+1, is the highest. This implies that the rate of mean reversion on h+1 has to be higher, in order to pull back the price to the level in hour h+1.

Restricted model (ii)
The estimates presented in the tables 4.9, 4.10 and 4.11 correspond with restricted model (ii).

μ_0	3.298 (0.020)***	μ_{12}	0.530 (0.023)***	α_0	0.760 (0.010)***
μ_1	-0.134 (0.012)***	μ_{13}	0.382 (0.017)***	β_1	-0.180 (0.021)***
μ_2	-0.342 (0.017)***	μ_{14}	0.367 (0.021)***	β_2	-0.366 (0.024)***
μ_3	-0.471 (0.020)***	μ_{15}	0.284 (0.020)***	β_3	0.045 (0.024)***
μ_4	-0.572 (0.024)***	μ_{16}	0.220 (0.020)***	β_4	0.070 60.024)***
μ_5	-0.573 (0.024)***	μ_{17}	0.208 (0.021)***	β_5	0.052 (0.011)***
μ_6	-0.410 (0.037)***	μ_{18}	0.428 (0.034)***	β_6	0.051 (0.021)***
μ_7	-0.287 (0.055)***	μ_{19}	0.341 (0.019)***	Adj.R^2	0.941
μ_8	-0.050 (0.062)	μ_{20}	0.284 (0.014)***	Durbin Watson	2.091
μ_9	0.191 (0.033)***	μ_{21}	0.222 (0.011)***	Log-LH	-8631.3
μ_{10}	0.369 (0.026)***	μ_{22}	0.145 (0.008)***		
μ_{11}	0.458 (0.024)***	μ_{23}	0.010 (0.010)***		

Standard errors are in parentheses. Significant at: ***99%, **95%, *90% confidence level. Number of observations: 8784

Table 4.9: SUR parameter estimates for the restricted model (ii) for APX prices

μ_0	3.236 (0.020)***	μ_{12}	0.469 (0.018)***	α_0	0.745 (0.010)***
μ_1	-0.110 (0.018)***	μ_{13}	0.378 (0.015)***	β_1	-0.198 (0.019)***
μ_2	-0.316 (0.023)***	μ_{14}	0.337 (0.018)***	β_2	-0.354 (0.021)***
μ_3	-0.448 (0.028)***	μ_{15}	0.269 (0.019)***	β_3	0.028 (0.022)***
μ_4	-0.535 (0.029)***	μ_{16}	0.218 (0.019)***	β_4	0.044 (0.022)***
μ_5	-0.501(0.026)***	μ_{17}	0.207 (0.018)***	β_5	0.045 (0.021)***
μ_6	-0.268 (0.026)***	μ_{18}	0.273 (0.017)***	β_6	0.061 (0.019)***
μ_7	-0.133 (0.034)***	μ_{19}	0.321 (0.015)***	Adj.R^2	0.958
μ_8	0.119 (0.033)***	μ_{20}	0.293 (0.013)***	Durbin Watson	2.082
μ_9	0.231 (0.029)***	μ_{21}	0.264 (0.013)***	Log-LH	-8348.9
μ_{10}	0.327 (0.020)***	μ_{22}	0.196 (0.011)***		
μ_{11}	0.385 (0.017)***	μ_{23}	0.154 (0.008)***		

Standard errors are in parentheses. Significant at: ***99%, **95%, *90% confidence level. Number of observations: 8784

Table 4.10: SUR parameter estimates for the restricted model (ii) for EEX prices

μ_0	3.278 (0.021)***	μ_{12}	0.363 (0.016)***	α_0	0.707 (0.010)***
μ_1	-0.193 (0.017)***	μ_{13}	0.319 (0.013)***	β_1	-0.184 (0.022)***
μ_2	-0.319 (0.020)***	μ_{14}	0.281 (0.014)***	β_2	-0.373 (0.025)***
μ_3	-0.425 (0.021)***	μ_{15}	0.223 (0.015)***	β_3	0.022 (0.025)***
μ_4	-0.560 (0.022)***	μ_{16}	0.171 (0.018)***	β_4	0.082 (0.025)***
μ_5	-0.676 (0.031)***	μ_{17}	0.155 (0.019)***	β_5	0.072 (0.025)***
μ_6	-0.401 (0.025)***	μ_{18}	0.215 (0.015)***	β_6	0.052 (0.022)***
μ_7	-0.240 (0.039)***	μ_{19}	0.271 (0.013)***	Adj.R^2	0.943
μ_8	0.014 (0.029)	μ_{20}	0.262 (0.011)***	Durbin Watson	2.083
μ_9	0.172 (0.028)***	μ_{21}	0.189 (0.009)***	LogLH	-8208.5
μ_{10}	0.266 (0.018)***	μ_{22}	0.136 (0.008)***		
μ_{11}	0.312 (0.016)***	μ_{23}	0.098 (0.006)***		

Standard errors are in parentheses. Significant at: ***99%, **95%, *90% confidence level. Number of observations: 8784

Table 4.11: SUR parameter estimates for the restricted model (ii) for PPX prices

This model restricts the freedom of the hourly-varying mean-reversion rate (such that α_h = 0 (h=1….24)) as specified in the stochastic component of the general model. When we compare the reported values of μ_h for the general model and the reported parameter values of this restricted model, the values are roughly the same. Furthermore, the pattern is similar. The estimates for μ_h are negative for hours 1 through 7 indicating the lower prices for off-peak delivery of power. Then prices for later hours and eventually prices decrease later in the evening. In this model, hourly prices revert back to their hourly mean price level with a constant speed throughout the day. The mean reversion rate level varies between the 0.707 for the PPX and 0.760 for the APX.

Restricted model (iii)

In tables 4.12, 4.13 and 4.14 we provide the estimates corresponding with the restricted model (iii). Here, the freedom of the hourly-varying parameters in the general model are restricted, such that μ_h=0 and α_h = 0 (h=1….24). The intra-day (hourly) dimension is in this model thus shows up in the hourly cross-sectional covariance matrix described by equation (4.4). From the α_h parameters listed in the tables, we observe that prices in weekends are lower than in weekdays, which is indicated by the negative β_1 and β_2 coefficient that are roughly around respectively -0.15 and -0.35. This implies that prices on the markets are on Saturdays €1.2 lower than the average price, and on Sunday even €1.4 lower. The value of the mean-level price estimate μ_0 is roughly around 3.4 across markets, which reflects an average price of €30 for 1 MWh of electricity.

μ_0	3.413 (0.019***	β_3	0.031 (0.026)	Adj.R^2	0.936
α_0	0.585 (0.010)***	β_4	0.082 (0.026)***	Durbin Watson	2.132
β_1	-0.153 (0.021)***	β_5	0.064 (0.025)***	Log-LH	-8788.0
β_2	-0.360 (0.025)***	β_6	0.051 (0.021)***		

Standard errors are in parentheses. Significant at: ***99%, **95%, *90% confidence level. Number of observations: 8784

Table 4.12: SUR parameter estimates for the restricted model (iii) for APX prices

μ_0	3.408 (0.019)***	β_3	0.010 (0.025)***	Adj.R^2	0.939
α_0	0.551 (0.010)***	β_4	0.052 (0.025)***	Durbin Watson	2.152
β_1	-0.181 (0.020)***	β_5	0.047 (0.024)***	Log-LH	-8383.9
β_2	-0.350 (0.024)***	β_6	0.064 (0.019)***		

Standard errors are in parentheses. Significant at: ***99%, **95%, *90% confidence level. Number of observations: 8784

Table 4.13: SUR parameter estimates for the restricted model (iii) for EEX prices

μ_0	3.366 (0.022)***	β_3	-0.012 (0.028)	Adj.R^2	0.926
α_0	0.495 (0.009)***	β_4	0.088 (0.028)***	Durbin Watson	2.199
β_1	-0.170 (0.022)***	β_5	0.067 (0.026)***	Log-LH	-8277.6
β_2	-0.374 (0.026)***	β_6	0.047 (0.022)**		

Standard errors are in parentheses. Significant at: ***99%, **95%, *90% confidence level. Number of observations: 8784

Table 4.14: SUR parameter estimates for the restricted model (iii) for PPX prices

4.4.3. Results model specification tests

To formally test whether the general model is a better model specification than either of the restricted versions we employ the likelihood ratio (LR) test given by equation (4.7). In table 4.15 we provide the results of testing the general model against all the restricted nested versions individually. The LR test statistic is Chi-square distributed under the null-hypothesis of correctly imposed restrictions. The number of degrees of freedom is set equal to the number of exclusion restrictions. Therefore the degrees of freedom that corresponds to the LR test statistic for testing the restricted version of model (i) and (ii) against the general specification, equals 23. The number of degrees of freedom corresponding to the LR test employed on the general model and the restricted version (iii), equals 46.

	APX	EEX	PPX
General model vs. Restricted (i)	136.4***	89.80**	19.80
General model vs. Restricted (ii)	-28.40	35.80**	-62.00
General model vs. Restricted (iii)	264.4***	105.8***	76.20***

The LR test statistic is Chi-square distributed. The critical values of the Chi-square distribution with 23 degrees of freedom at the ***99%, **95% and *90% confidence levels are respectively 41.64, 35.17 and 32.00. The critical values of the Chi-square distribution with 46 degrees of freedom at the ***99%, **95% and *90% confidence levels are 71.20, 62.83 and 58.64.

Table 4.15: LR model specification test: general model versus restricted nested models

From the LR test statistics reported in the bottom row of table 4.15, we can conclude that we have to reject the null-hypothesis of correctly imposed restrictions as specified in restricted model (iii). This implies that dropping the hourly varying parameters from the general model, as is done in the restricted (iii) version, leads to erroneous results. From the left column we can see that a panel model that allows for hourly-varying mean price levels and has a covariance matrix specified by equation (4.4), describes the APX hourly price dynamics the best (compared to the restricted model provided in this Chapter). The LR test statistics obtained from testing the general model against the restricted version (ii) show that the hourly mean-reversion parameters in the general model are not important to describe the hourly dynamics in the APX market. From the middle column in the table, we can see that the general model describes the EEX power price characteristics relatively the best. From the right column in the table, we can conclude that dropping out either the hourly-mean reversion parameters *or* the hourly mean level parameters from the general model, does not lead to a fall in the log-likelihood value that is large enough to conclude that the dropped variables are important for modeling hourly price dynamics in the PPX market.

4.5 Concluding remarks

This Chapter proposes a panel framework to model the dynamics in hourly electricity prices in day-ahead markets. We have examined the characteristics of hourly prices for day-ahead delivery of electricity in the APX, EEX and PPX markets.

As many researchers have concentrated mainly on daily average prices, we present a framework to describe the dynamics on an intra-day basis. Hourly electricity prices do not follow a time series process but are in fact a panel of 24 cross-sectional hours that vary from day to day. This is due to the microstructure of many day-ahead, where prices for all hours are quoted at the same moment on a day.

The empirical results show that hourly electricity prices in day-ahead markets mean-revert around an hourly specific mean price level and that a block structured cross-sectional correlation pattern is apparent. We also provide evidence obtained from one market in our analysis (EEX) that the speed of mean-reversion is different over the hours (especially in super-peak hours). Examination of the cross-sectional pattern between hourly prices discloses that prices in peak-hours correlate highly among each other and the same holds

for prices in off-peak hours. There is much less correlation between peak and off-peak hours. This effect can be explained by the differences in reserve capacity between the two blocks. The lower reserve capacity in the peak hours implies that the prices in those hours are more volatile and exhibit more spikes than prices in off-peak hours.
Understanding the characteristics of hourly prices is important as many agents in the electricity markets are exposed to hourly variation. Power generation plants let their nomination depend on the expected prices for electricity throughout the day. Companies that use electricity in a certain profile through the day that cannot be resembled by standard baseload and peakload contracts might have a demand for contracts that deliver only in a few hours of the day. To valuate these contracts market makers need to assess the expectations and risks for those specific hours and cannot rely on daily average prices only. Other applications of the hourly price model can be found in risk management, contract structuring and derivative pricing (e.g. hourly power options are currently traded in the U.S. markets, and to a lesser extent in the European markets). The general model can be used for making simulations and the importance of having different mean-reversion levels and the correlation matrix helps to get a better assessment of the risks faced from exposures to dynamics in specific hours.

4.6 Appendix

	1	2	3	4	5	6	7	8	9	10	11	12
1	1.000											
2	**0.870**	1.000										
3	**0.777**	**0.905**	1.000									
4	**0.647**	**0.801**	**0.888**	1.000								
5	**0.644**	**0.798**	**0.868**	**0.935**	1.000							
6	0.330	0.442	**0.510**	**0.558**	**0.657**	1.000						
7	0.029	0.258	0.359	0.383	0.480	**0.616**	1.000					
8	-.053	0.168	0.284	0.299	0.382	0.364	**0.856**	1.000				
9	-.058	0.225	0.307	0.337	0.417	0.449	**0.698**	**0.696**	1.000			
10	-.030	0.151	0.221	0.233	0.281	0.342	0.457	0.450	**0.762**	1.000		
11	-.070	0.049	0.055	0.084	0.147	0.254	0.329	0.334	**0.630**	**0.844**	1.000	
12	-.131	-.040	-.043		0.046	0.201	0.279	0.273	**0.518**	**0.698**	**0.883**	1.000

Here we report only those elements that are significantly different from zero at a 99% confidence interval by employing a Fisher-test. The correlation numbers bigger than 0.5 are reported boldfaced; non-significant correlations are left blank.

Table A4.1. Part a (see textbox 3.1) of cross-sectional correlation matrix of the general model for the APX market

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
13		0.098	0.100	0.098	0.169	0.264	0.328	0.298	**0.527**	**0.697**	**0.818**	**0.838**
14	-.122		0.045	0.082	0.135	0.251	0.325	0.313	**0.588**	**0.765**	**0.824**	**0.836**
15	-.138	0.035	0.082	0.112	0.186	0.290	0.381	0.383	**0.638**	**0.705**	**0.717**	**0.733**
16	-.133	0.059	0.113	0.142	0.220	0.322	0.438	0.444	**0.676**	**0.670**	**0.667**	**0.658**
17	-.098	0.057	0.108	0.137	0.201	0.250	0.317	0.351	**0.535**	**0.530**	**0.527**	**0.532**
18	-.173	-.053		0.032	0.050	0.037	0.109	0.168	0.280	0.295	0.340	0.341
19	0.196	0.179	0.166	0.105	0.146	0.111			0.049	0.133	0.163	0.114
20	0.339	0.271	0.211	0.182	0.220	0.116	-.057	-.096	-.080	0.061	0.099	0.060
21	0.496	0.410	0.336	0.290	0.307	0.156	-.060	-.151	-.174	-.063	-.062	-.058
22	**0.521**	0.373	0.314	0.268	0.276	0.147	-.138	-.233	-.214	-.120	-.124	-.123
23	**0.503**	0.297	0.235	0.190	0.154		-.349	-.407	-.341	-.236	-.198	-.176
24	**0.643**	**0.541**	0.473	0.402	0.402	0.204	-.101	-.218	-.075			

Here we report only those elements that are significantly different from zero at a 99% confidence interval by employing a Fisher-test. The correlation numbers bigger than 0.5 are reported boldfaced; non-significant correlations are left blank.

Table A4.2. Part b (see textbox 3.1) of 24 x 24 cross-sectional correlation matrix of the general model for the APX market

	13	14	15	16	17	18	19	20	21	22	23	24
13	1.000											
14	**0.873**	1.000										
15	**0.770**	**0.900**	1.000									
16	**0.714**	**0.801**	**0.888**	1.000								
17	**0.505**	**0.640**	**0.739**	**0.821**	1.000							
18	0.288	0.400	0.417	0.440	**0.535**	1.000						
19	0.113	0.182	0.173	0.208	0.268	**0.544**	1.000					
20	0.093	0.090	0.091	0.137	0.183	0.210	**0.641**	1.000				
21		-.037	-.035	-.028	0.032	0.032	0.387	**0.701**	1.000			
22	-.038	-.085	-.075	-.084	-.070	-.045	0.292	**0.613**	**0.772**	1.000		
23	-.089	-.160	-.185	-.218	-.192	-.078	0.214	0.425	**0.573**	**0.782**	1.000	
24	0.102		0.036		-.031		0.314	**0.545**	**0.611**	**0.733**	**0.766**	1.000

Here we report only those elements that are significantly different from zero at a 99% confidence interval by employing a Fisher-test. The correlation numbers bigger than 0.5 are reported boldfaced; non-significant correlations are left blank.

Table A4.3. Part c (see textbox 3.1) of cross-sectional correlation matrix of the general model for the APX market

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1	1.000											
2	**0.890**	1.000										
3	**0.830**	**0.933**	1.000									
4	**0.765**	**0.854**	**0.924**	1.000								
5	**0.599**	**0.627**	**0.670**	**0.735**	1.000							
6	**0.604**	**0.662**	**0.694**	**0.673**	**0.712**	1.000						
7	0.274	0.316	0.377	0.385	**0.658**	**0.808**	1.000					
8	0.167	0.215	0.277	0.281	0.339	**0.655**	**0.767**	1.000				
9	0.191	0.237	0.280	0.253	0.307	**0.593**	**0.729**	**0.903**	1.000			
10	0.220	0.259	0.268	0.227	0.238	**0.536**	**0.601**	**0.772**	**0.861**	1.000		
11	0.246	0.269	0.246	0.205	0.209	0.481	**0.505**	**0.649**	**0.748**	**0.916**	1.000	
12	0.193	0.148	0.128	0.084	0.105	0.354	0.403	**0.553**	**0.665**	**0.829**	**0.898**	1.000

Here we report only those elements that are significantly different from zero at a 99% confidence interval by employing a Fisher-test. The correlation numbers bigger than 0.5 are reported boldfaced; non-significant correlations are left blank.

Table A4.4. Part a (see textbox 3.1) of cross-sectional correlation matrix of the general model for the PPX market

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
13	0.275	0.229	0.205	0.157	0.164	0.404	0.417	**0.543**	**0.638**	**0.823**	**0.899**	**0.919**
14	0.255	0.255	0.224	0.171	0.163	0.426	0.445	**0.579**	**0.682**	**0.869**	**0.931**	**0.896**
15	0.218	0.234	0.202	0.145	0.156	0.409	0.476	**0.628**	**0.712**	**0.868**	**0.890**	**0.824**
16	0.240	0.255	0.248	0.204	0.233	**0.510**	**0.584**	**0.744**	**0.818**	**0.836**	**0.817**	**0.748**
17	0.221	0.255	0.271	0.227	0.236	0.479	**0.565**	**0.706**	**0.753**	**0.763**	**0.725**	**0.637**
18	0.279	0.285	0.309	0.282	0.245	0.474	0.433	**0.576**	**0.573**	**0.698**	**0.658**	**0.574**
19	0.283	0.267	0.272	0.256	0.213	0.365	0.299	0.445	0.431	**0.567**	**0.568**	0.496
20	0.386	0.332	0.336	0.331	0.260	0.379	0.248	0.302	0.280	0.441	0.461	0.431
21	**0.566**	0.480	0.476	0.469	0.331	0.438	0.215	0.233	0.194	0.343	0.403	0.375
22	**0.584**	0.487	0.473	0.460	0.326	0.406	0.135	0.079	0.067	0.247	0.337	0.330
23	**0.603**	**0.511**	0.469	0.448	0.294	0.268		-.054	-.035	0.181	0.297	0.321
24	**0.599**	**0.553**	**0.504**	0.479	0.329	0.307	0.050		0.049	0.294	0.387	0.349

Here we report only those elements that are significantly different from zero at a 99% confidence interval by employing a Fisher-test. The correlation numbers bigger than 0.5 are reported boldfaced; non-significant correlations are left blank.

Table A4.5. Part b (see textbox 3.1) of cross-sectional correlation matrix of the general model for the PPX market

	13	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
13	1.000											
14	**0.922**	1.000										
15	**0.854**	**0.938**	1.000									
16	**0.779**	**0.839**	**0.898**	1.000								
17	**0.680**	**0.752**	**0.817**	**0.881**	1.000							
18	**0.657**	**0.731**	**0.764**	**0.745**	**0.810**	1.000						
19	**0.592**	**0.638**	**0.647**	**0.599**	**0.676**	**0.858**	1.000					
20	**0.523**	**0.541**	**0.535**	0.493	**0.548**	**0.731**	**0.832**	1.000				
21	0.473	0.471	0.446	0.417	0.427	**0.572**	**0.635**	**0.816**	1.000			
22	0.425	0.406	0.364	0.332	0.297	0.424	0.487	**0.713**	**0.900**	1.000		
23	0.404	0.379	0.327	0.258	0.228	0.356	0.441	**0.656**	**0.835**	0.903	1.000	
24	0.472	0.470	0.432	0.330	0.315	0.455	**0.544**	**0.675**	**0.779**	**0.808**	**0.898**	1.000

Here we report only those elements that are significantly different from zero at a 99% confidence interval by employing a Fisher-test. The correlation numbers bigger than 0.5 are reported boldfaced; non-significant correlations are left blank.

Table A4.6 Part c (see textbox 3.1) of cross-sectional correlation matrix of the general model for the PPX market

Chapter 5: Electricity futures and forward prices[41]

-Empirical evidence on forecast power, risk premia and time-to-maturity effect-

5.1 Introduction

The cost-of-carry relationship[42] that links the spot price of an underlying storable asset to its forward- or future price cannot be used for deriving the fair value of power derivatives. The inability to link the spot and derivative price as a no-arbitrage condition stems from the non-storability of electricity; electricity forward- or future traders cannot make their portfolio risk neutral by trading these derivatives on one side while maintaining a position in the underlying commodity for the time until delivery on the other side. Note that throughout this Chapter we do not distinguish between forward and futures prices, as these prices are very close to each other in practice.

In this Chapter, we adopt an alternative approach that relies on an equilibrium argument to link spot prices with forward-, or futures prices simultaneously: the forward price of electricity represents the sum of the expected future spot price in the delivery period, and a risk premium. The first term embeds expectations about the future spot price, as the forward is in fact a forward-looking contract that locks in the future price of the underlying spot. The second term, the premium, could be thought of as a compensation component that is captured in the forward price for the spot price movements (price risk) that both parties insulate themselves from by entering into the contract (Hull, 2002). Here the risk premium is defined as the difference between the current forward price and the expected future spot price.

Recently, several papers have examined the risk premium in power forward and future contracts. Bessembinder and Lemmon (2002) postulate an equilibrium model in which different agents are exposed to economic risks (i.e. price and demand risks). They document evidence from the Pennsylvania, New-Jersey, Maryland (PJM) market that the forward price increases with average demand load and find a positive premium for power delivery in summer months. Longstaff and Wang (2004) provide evidence consistent with the findings of Bessembinder and Lemmon (2002), by conducting a high-frequency analysis on the U.S. market. They show that the day-ahead risk premia vary throughout the day and can be explained by economic risk factors such as volatility in demand, revenues and spot prices. Karakatsani and Bunn (2005) provide insight in risk premiums in the British market and find that positive risk premiums are dominant in peak hours (compensating flexible generators for bearing spot price risk) and negative premia in off-peak hours. Karakatsani and Bunn (2005) explain that the negative risk premia are caused by the less flexible baseload power generators that need to comply to strict technical

[41] This Chapter is partly based on: R. Huisman and C. Huurman (2006) "Risk premiums in power forwards", Working paper RSM Erasmus University. We thank participants at Energy Markets Group seminar at London Business School (6 October 2005) for valuable comments. Furthermore, we thank Eric de Koning for processing part of the data.

[42] The cost-of-carry relationship shows that the price of a standard derivative contract today, for example a next-month delivery forward, should be equal to the costs of an investment strategy in which the investor decides to borrow money against the interest rate, buy the underlying commodity today, and store it. Then in the next month from t, the commodity will be sold in the market in order to pay back the loan including interest, with the income on the underlying commodity (Hull, 2002).

regulations and sell their output in off-peak hours at a discount in order to avoid costs for ramping down and ramping up later.
In this Chapter, we do not focus on potential factors that affect (the size and sign of) forward premia. We make an attempt to disclose to what extent observed electricity forward-, and futures prices can be interpreted as a risk premium and as an expectation of the spot price in the delivery period, and how these components evolve over time. This issue is relevant, as market makers need to assess how the fractions of expectations and risks incorporated in the prices of contracts with different maturities evolve over time
To do so, we follow the framework proposed by Fama (1984) that allows for joint measurement of both the forecast component and premium component. We apply the Fama model on price data of forward-, and future contracts with different maturity horizons. In this study we attempt to shed light on the relationship between time-to-maturity and the risk premium component and forecast component embedded in electricity forward prices.
In particular, the reported empirical evidence that we obtain from *monthly* electricity forward prices of contracts with a time-to maturity ranging from one-month up to six-months, discloses that the risk premium component increases with maturity when the contracts rolls to the expiration date as close as one month. This time to maturity pattern is consistent with commodity derivative price theory (Samuelson (1965)).
We also we apply the Fama model to disentangle the time-to-maturity effect embedded in the premium-, and forecast component embedded in *daily* electricity forward prices. We do this for the contracts in our sample with the shortest horizon, being month-ahead contracts. We disclose that the fraction of the spot price forecast component increases when we roll from one trading day to the next up to a few trading days before expiration, which goes in line with the derivative price theory that forward prices converge to its underlying spot price very close to expiration and in the delivery period (Hull, 2002).
We obtain both price data for the abovementioned forward contract maturities and spot price data of day-ahead contracts from three markets: The European Energy Exchange (EEX) in Frankfurt, the European Energy Derivatives Exchanges (ENDEX) and Amsterdam Power Exchange (APX) in Amsterdam, and the Nordic Power Exchange (NPX) in Oslo.
The Chapter is structured as follows. Section 5.2 sets out the Fama methodology and presents the hypotheses to test for the time-to-maturity effect in forward prices. Section 5.3 presents the data set. Section 5.4 provides the estimation results. Section 5.5 concludes.

5.2 Disclosing the time-to-maturity pattern in electricity futures and forward prices

In this section we outline the methodology to gain insight whether the fractions of risk premium and price predictive power to future spot prices are significant, and disclose a time-to-maturity pattern that goes in line with derivative price theory.

5.2.1 Fama model

Let $F_T(t)$ be the forward price per MWh quoted at time t for delivery of 1 MWh power in each hour of the future delivery period T. Let $E_t(S_T)$ be the expectation at time t that representative traders have for the spot price in the delivery period T. Let $RP_T(t)$ be the risk premium per MWh for delivery of power in period T quoted at time t. The forward price observed at time t equals:

$$F_T(t) = E_t(S_T) + RP_T(t) \qquad (5.1)$$

To gain insight in the informational content of forward prices, we subtract the current spot price (observed at time t) from both sides in equation (5.1). If S(t) represents the current spot price of power, we obtain the following expression:

$$F_T(t) - S(t) = E_t(S_T) - S(t) + RP_T(t) = [E_t(S_T) - S(t)] + [F_T(t) - E_t(S_T)] \qquad (5.2)$$

Equation (5.2) shows that the forward basis observed at time t (on the left-hand side of the equation), can be decomposed in two components that are denoted in square brackets on the right-hand side of the equation: the expected change in the spot price and the realized risk premium.
Fama applies the following regression models to disentangle risk premia and spot price expectations on future price data:

$$S_T - S(t) = \alpha_0 + \beta_0 (F_T(t) - S(t)) + \sigma_0\theta_t, \text{ where } \theta_t \sim IID\ (0, 1) \qquad (5.3)$$

$$F_T(t) - S_T = \alpha_1 + \beta_1 (F_T(t) - S(t)) + \sigma_0\omega_t, \text{ where } \omega_t \sim IID\ (0, 1) \qquad (5.4)$$

Evidence that the slope coefficient estimate β_0 in equation (5.3) is positive and significant would imply that the basis contains information about the expected change in the spot price. Evidence that the slope coefficient estimate β_1 in equation (5.4) is positive and significant would imply that the basis contains information about the realized risk premium. Power to forecast ex-post risk premia is evidence of time-varying ex-ante premia. Because the independent variables of the equations add up to the basis, the α's and β's add up to respectively 0 and 1. Henceforth, in equations (5.3) and (5.4), basis variation is by definition allocated to (a mix) of the dependent variables in equation (5.3) and equation (5.4). This can yield statistically unreliable results. In particular, this typically occurs when basis variation is low relative to the variation of the dependent variables of model (5.3) and model (5.4) (Fama, 1984). Before estimating the regressions, we first have to examine the relative magnitude of the standard deviation estimates of the model's variables.

A point worth emphasizing is that in electricity markets, the delivery under the forward- or future contracts is typically uniformly spread over the delivery period. For instance, next-month baseload (peakload) contracts secure the delivery of 1 MWh of electricity in each baseload (peakload) hour in the first upcoming month from the observation date t. Therefore the holder of the contract is exposed to the differential between the baseload (peakload) forward price and the arithmatic average of the hourly spot prices in the delivery month. We therefore use the average day-ahead price calculated over all baseload (peakload) hours in the delivery month, when we construct the basis-, expected spot price change-, and risk premium observations that correspond with the forward contract under consideration.

What to expect?
Fama (1984) reports empirical evidence, obtained from nine forward exchange rates (Japan, Canada, UK and six major European currencies), that variation in forward rates predominantly stems from variations is premiums. In Fama and French (1987) the framework has been applied to assess the forecast power and risk premia embedded in futures prices obtained from twenty-one different (storable) commodities. The empirical findings of Fama and French (1987) may provide us with more insights what we can

expect from the extent of explanatory value of the electricity forward basis. They discuss what economic features explain the differences in basis variation across a wide range of (storable) M2, M6 and M10 commodity forward contracts (delivers on respectively 2nd , 6th and 10th month from observation date): ten agricultural-, five animal- two wood-, and four metal products.
They show that forward contracts on metals primarily track the interest rates, while basis variation in the agricultural- and wood contracts is predominantly driven by the warehousing and convenience yields. High inventory levels closely relate to low variation in the basis and expected spot price changes, simply because inventory functions as a buffer for demand and supply shocks. Therefore, the regression model fails to identify the source (the realized risk premia or expected spot price changes) of the nonzero basis variation for all metals. In contrast, animal products and some agricultural products, have high storage costs due to bulk and decay ability, which may lead to lower levels of inventory and therefore high basis variation. Since basis variation is substantial, the regressions have a good chance of reliably assigning basis variation to either spot price forecast and/or expected premia. They indeed find a clear distinction between risk premia and expected spot changes for these products. Since in electricity markets inventory levels cannot be used to smoothen out demand and supply shocks as well, it is logical to expect high variation in the basis variation and expected spot price changes. We therefore believe that the equations (5.3) and (5.4) have a good chance of reliably assigning basis variation in electricity forwards to either spot price forecast and/or expected premia. Therefore our best bet is to find empirical evidence that indicates that the electricity forward basis incorporates either strong forecasting power or strong expected risk premia.
Note that most commodity contracts examined in Fama and French (1987) typically have a delivery period of three to four weeks. They assume that it matures on the first trading day of the delivery month. Furthermore they use future prices of maturing contracts as a proxy for spot prices since good spot price data is not available, contrary to our case.
A final point worth emphasizing is that Fama and French report weak statistical evidence for the explanatory power of the basis to spot price forecasts and expected risk premia; only two commodities show significant forecast power and expected risk premia. In an attempt to increase the statistical power of the test, Fama and French combine commodities into portfolios. They don't find strong empirical evidence of risk premia and forecast power in the portfolio setting either. They argue that the marginal evidence that they provide is due to the relatively small series[43] of available data. This argument is questionable, because for some commodities Fama and French report empirical evidence of good forecast power embedded in forward prices, while the sample used to obtain this evidence is as small as 35 observations.

5.2.2 Hypotheses 1 and 2

As discussed in the previous section, we apply the equations (5.3) and (5.4) for joint-measurement of the explanatory value of the risk premium and forecast component embedded in electricity forward prices. We do this for different contract maturities, and attempt to gain understanding whether we can disclose a time-to-maturity pattern in the

[43] In a small sample, shocks in spot prices will yield high variation in the basis compared to any forward risk premium, hence this results in low statistical power in small samples (Bessembinder and Lemmon, 2002).

size of these components that is consistent with derivative price theory. We will now formulate the hypotheses that we have constructed based on the theory.

Samuelson effect

Samuelson (1965) shows that when spot prices are mean-reverting and arbitrage opportunities are absent, the return volatility of forward contracts rises when the contracts rolls to its expiration date. This effect has become known as the Samuelson effect, and several studies have documented (weak to strong) evidence in support of the existence of this pattern in many commodity prices: See Bessembinder et al (1996) for an excellent critical review. In figure 5.1 we can observe this effect in electricity markets. From the figure we can see the prices of forward contracts that secure delivery in the month August 2005, which we obtain from the EEX forward curve.

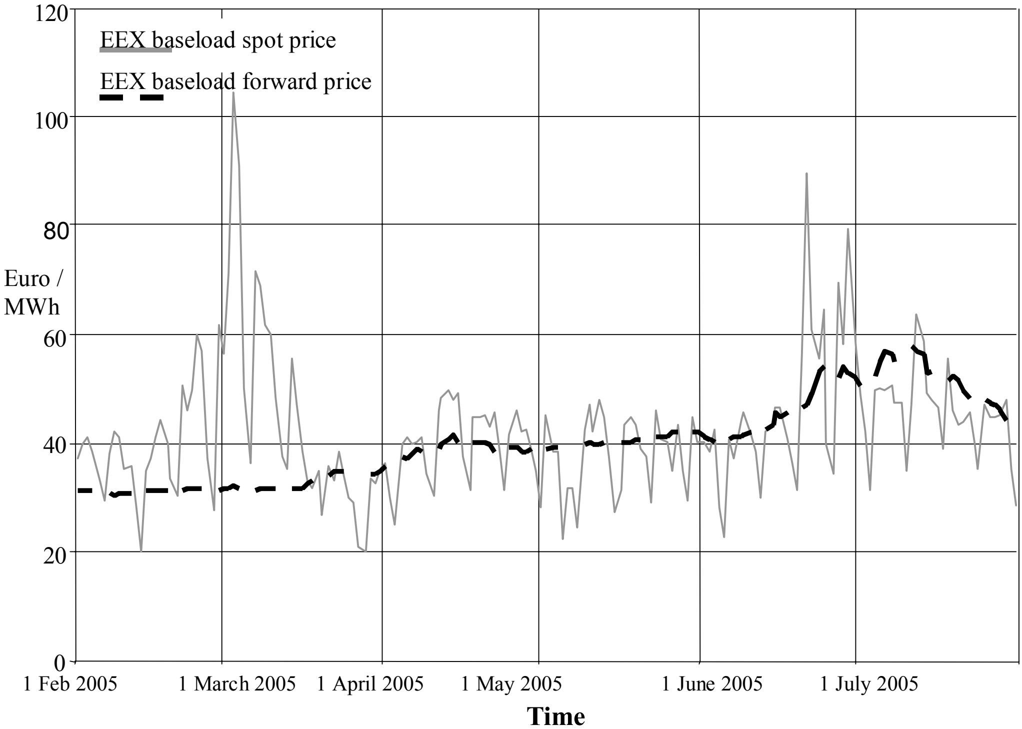


Figure 5.1 EEX baseload spot prices, and EEX baseload futures prices for contracts that mature in August 2005.

We can observe that the day-ahead EEX prices, also displayed in the figure, are more volatile compared with the futures prices. This figure reflects a general development of (monthly) futures prices. We see that when the time-to-maturity is about five to six months, the futures prices do not seem to react to the spot prices. However, when the time to delivery is approached, the forward price responses more accurately to the spot prices.

This behaviour can be addressed to the mean-reverting behaviour[44] of the underlying spot price process, and has been documented for many other commodities than power.
Let's assume that today is a certain day in February 2005. Would a spot price shock around this period affect our expectation about the price level six months from now in August 2005? It is well-known that spot price shocks in electricity die out quickly (Pilipovic, 1998), hence the expectation around February is that the price has moved back to the long-term equilibrium mean by the time the expiration date of an M6 contract is approached. When we get closer to expiration however, the chance that the spot price oscillates around its mean will be lower. To compensate for the rise in the price volatility when the contract rolls to his expiration date maturity, the investors in the forward contract expect a higher risk premium. Note that in most financial markets, a longer time horizon implies that investors require a higher risk premium when the spot price process is assumed to follow a random walk instead of a mean-reverting process. This can be explained by the fact that when the price path is given by a random walk process, the price is more uncertain one month in the future than a day in the future. However, when a mean-reverting price process is assumed, the uncertainty incorporated in the price one month-ahead and one day-ahead is roughly the same.

When we examine the one-factor, and two-factor mean-reverting models to price power derivatives along in Lucia and Schwartz (2002), we observe the presence of the Samuelson-effect in the price models. In particular, we can split the risk neutral forward price into a risk-neutral expected value of the maturity spot price, and a risk premium component that decreases with time to maturity (see Appendix A5.1-A.5.3 for derivation). Finding evidence in support of the existence of the Samuelson effect in electricity markets, is therefore also consistent with the Lucia and Schwartz model. We can formulate the following hypothesis:
H1: "The risk premium embedded in electricity forwards decreases with time to maturity"

Price convergence
In standard derivative pricing theory spot prices are linked to forward prices as a no-arbitrage condition. Let's consider a representative agent. Her motive is to exploit arbitrage opportunities (make risk-free profit) in the market. Furthermore consider scenario (i): the futures price is above the spot price price *during* the delivery period. And consider scenario (ii): the futures price is below the spot price price *during* the delivery period. The following strategy would yield a risk-free profit in (i): (1) Sell a futures/ forward contract, (2) buy the underlying asset and (3) make delivery to close the position. The opposite trading strategy would yield a risk-free profit in (ii). When arbitrageurs recognize this opportunity and act upon it, the futures price will fall in (i), rise in (ii), and the opportunity will be traded away. Therefore the derivative price is expected to converge to the spot price of the underlying asset when the delivery period is reached (Hull, 2002).[45]

[44] The tendency of the spot price to return to it's long-term mean after a price shock has occurred.
[45] Observe that when there exists a time gap between step (2) and (3) such that the underlying asset needs to be stored, the above strategies cannot been implemented for a non-storable commodity as electricity. As a result, the no-arbitrage condition cannot be meaningfully applied. The question arises what mechanism keeps electricity spot and forward prices in incomplete markets. In incomplete markets, one can by definition not obtain risk-free prices through the no-arbitrage condition.

We can now formulate the following hypothesis:
H2: “The electricity forward price converges to the underlying spot price”.

5.3 Sample and data description

We study the relationship between forward prices and day-ahead prices from three different national markets. We derive price data from the German EEX, the Dutch APX (day-ahead contracts only) and ENDEX (forward contracts only), and the Scandinavian exchange NPX.[46] We refer to Chapter 1, for a general introduction on these markets.

5.3.1 Monthly sample to test hypothesis 1

The German and Dutch forward data is obtained for the respective periods 1 July 2002 to 1 September 2005, and 3 February 2003 to 1 July 2005. From the EEX market, we include forward price data from six contract maturities in our sample: M1, M2, ….to M6 contracts. The forward price sample obtained from ENDEX, consists of price observations of M1, M2 and M3 contracts. The length in forward curve between the Dutch and German forward price sample differs because M4, M5 and M6 contracts were traded on ENDEX as of July 2004, hence the number of price observations is too small to include for the regression analysis employed on the individual maturity samples (10 or less price observations for each contract maturity). The sample that we examine consists of the closing prices on the first trading days[47] of each month in our sample. From the EEX we obtain daily day-ahead prices over the period 1 June 2002 to 31 October 2005, being 1188 daily day-ahead prices. From the APX we obtain 974 daily price observations from 1 February 2003 to 31 August 2005, being 974 daily price observations. We use this data to calculate for each month the average day-ahead price in baseload and peakload hours. Since baseload (peakload) M-contracts secure the delivery of 1 MWh for the derivative price $F_T(t)$ in each baseload (peakload) hour of the delivery month T, we assume this average price to be a good proxy for the expected spot price S_T in equation (5.3). Using the same line of reasoning, we use the average day-ahead price over a 30-day period starting from day t-30 to t, as a proxy for S(t) in the basis. Hence, in this way we created an EEX sample of 39 baseload and 39 peakload M1 basis-, M1 risk premia- and M1 expected spot price change observations. The APX/ENDEX sample consists of 30 baseload and 30 peakload M1 basis-, M1 risk premia- and M1 expected spot price change observations. Because the time to maturity increases with one month when we move from M1 contracts, to M2 contracts to the next, the number of observations decreases with one accordingly in the sample.
In the tables 5.1 to 5.9, we provide the descriptive statistics of the variables in the Fama equations (5.3) and (5.4), for the German data (table 5.1 to 5.6) and Dutch data (table 5.7 - 5.9). From the tables 5.1 to 5.9 we clearly observe the differences between baseload and peakload contracts. The average basis and realized risk premia of peak load contracts are, as expected, higher for the peak load forwards relative to base load contracts reflecting the higher variance of day-ahead prices in peak hours.

[46] Data is available at www.eex.de, www.apx.nl, www.endex.nl and www.nordpool.no. Until recently, data of the Dutch market could be downloaded from the website without subscription.
[47] Forward contracts are only traded on weekdays. In the weekend the derivative exchange is closed.

	Baseload			Peakload		
	$S_T - S(t)$	$F_T(t) - S(t)$	$F_T(t) - S_T$	$S_T - S(t)$	$F_T(t) - S(t)$	$F_T(t) - S_T$
Mean	0.791	1.574	0.782	0.806	8.525	7.719
Std. Deviation	6.657	5.161	7.079	9.121	7.973	10.68
Number of observations: 39. Data is in €/MWh.						

Table 5.1: Descriptive statistics of monthly EEX M1 price data

	Baseload			Peakload		
	$S_T - S(t)$	$F_T(t) - S(t)$	$F_T(t) - S_T$	$S_T - S(t)$	$F_T(t) - S(t)$	$F_T(t) - S_T$
Mean	0.845	1.220	0.375	0.926	8.490	7.564
Std. Deviation	6.738	6.259	7.057	9.212	9.785	10.99
Number of observations: 38. Data is in €/MWh.						

Table 5.2: Descriptive statistics of monthly EEX M2 price data

	Baseload			Peakload		
	$S_T - S(t)$	$F_T(t) - S(t)$	$F_T(t) - S_T$	$S_T - S(t)$	$F_T(t) - S(t)$	$F_T(t) - S_T$
Mean	0.708	0.492	-0.215	0.798	7.720	6.922
Std. Deviation	6.777	6.738	7.226	9.305	10.61	11.22
Number of observations: 37. Data is in €/MWh.						

Table 5.3: Descriptive statistics of monthly EEX M3 price data

	Baseload			Peakload		
	$S_T - S(t)$	$F_T(t) - S(t)$	$F_T(t) - S_T$	$S_T - S(t)$	$F_T(t) - S(t)$	$F_T(t) - S_T$
Mean	0.762	-0.378	-1.140	0.901	6.743	5.842
Std. Deviation	6.865	6.588	7.052	9.416	10.13	10.53
Number of observations: 36. Data is in €/MWh.						

Table 5.4: Descriptive statistics of monthly EEX M4 price data

	Baseload			Peakload		
	$S_T - S(t)$	$F_T(t) - S(t)$	$F_T(t) - S_T$	$S_T - S(t)$	$F_T(t) - S(t)$	$F_T(t) - S_T$
Mean	0.695	-0.742	-1.437	-0.506	5.581	6.087
Std. Deviation	10.42	9.611	6.339	14.53	13.97	9.853
Number of observations: 35. Data is in €/MWh.						

Table 5.5: Descriptive statistics of monthly EEX M5 price data

	Baseload			Peakload		
	$S_T - S(t)$	$F_T(t) - S(t)$	$F_T(t) - S_T$	$S_T - S(t)$	$F_T(t) - S(t)$	$F_T(t) - S_T$
Mean	1.801	0.078	-1.723	0.810	6.808	5.998
Std. Deviation	10.03	8.547	5.935	14.02	13.00	9.263
Number of observations: 32. Data is in €/MWh.						

Table 5.6: Descriptive statistics of monthly EEX M6 price data

	Baseload			Peakload		
	$S_T - S(t)$	$F_T(t) - S(t)$	$F_T(t) - S_T$	$S_T - S(t)$	$F_T(t) - S(t)$	$F_T(t) - S_T$
Mean	0.978	2.258	1.280	0.353	12.34	11.99
Std. Deviation	22.75	21.42	15.52	33.45	32.73	23.89
Number of observations: 30. Data is in €/MWh.						

Table 5.7: Descriptive statistics of monthly APX/ENDEX M1 price data

	Baseload			Peakload		
	$S_T - S(t)$	$F_T(t) - S(t)$	$F_T(t) - S_T$	$S_T - S(t)$	$F_T(t) - S(t)$	$F_T(t) - S_T$
Mean	1.862	2.533	0.671	1.354	12.64	11.29
Std. Deviation	23.39	20.74	15.05	34.17	30.72	22.71
Number of observations: 29. Data is in €/MWh.						

Table 5.8: Descriptive statistics of monthly APX/ENDEX M2 price data

	Baseload			Peakload		
	$S_T - S(t)$	$F_T(t) - S(t)$	$F_T(t) - S_T$	$S_T - S(t)$	$F_T(t) - S(t)$	$F_T(t) - S_T$
Mean	2.616	1.801	-0.815	2.161	11.00	8.840
Std. Deviation	25.84	20.03	14.90	38.29	28.86	21.73
Number of observations: 28. Data is in €/MWh.						

Table 5.9: Descriptive statistics of monthly APX/ENDEX M3 price data

In the previous section we mentioned that because variation in the basis is by definition allocated to (a mix) of the dependent variables in equation (5.3) and (5.4), this can yield statistically unreliable results. As said, this occurs when basis variation is low relative to the variation in spot price change ($S_T - S(t)$), and realized risk premium ($F_T(t) - S_T$).
From the tables 5.1 to 5.9, we observe that the standard deviations of the basis, the ex-post risk premium and the spot price change are substantial and of the same magnitude. We conclude from these estimates, that the equations (5.3) and (5.4) can reliably assign basis variation to either spot price changes or time-varying risk premia.

5.3.2 Daily sample to test hypothesis 2
From the EEX we obtain closing prices of M1 baseload- and peakload futures contracts for the sample period 1 July 2002 to 30 September 2005. Note that we extend the monthly EEX sample analyzed above, with market data observed on all other trading days of the month as well. From the NPX we derive closing prices of M1 baseload forward contracts for the sample period 1 July 2002 to 30 September 2005. Note that the NPX does not distinguish peakload prices from baseload prices.
In order to investigate the convergence of the electricity forward price to the expected spot price through employing the joint regression equation (5.3) and (5.4) simultaneously, we split our three (EEX baseload-, EEX peakload-, and NPX sample) samples into 17 subsets each of which represents observations on the n^{th} trading day of each month. As mentioned before, the EEX and NPX are closed during weekends. We estimate the parameters of equation (5.3) and (5.4) on the sub sample data of the first-trading day of the month observations only, the second trading day of the month observations only etcetera. Here n = 1, 2,..17. We have excluded the price observations of the 18^{th} trading day in the month of our analysis, because the sample size is too small. We calculated for each month the average day-ahead price in base load and peak load hours. We use the average day-ahead price over the period t-30 to t as a proxy for the current spot price S(t). Here t represents the trading day of the month. In this way the basis reflects the fact that the information set of an agent updates from one day to another (a 30 day moving window). In this way we created an EEX baseload (peakload) sample of 39 baseload (peakload) basis, 39 risk premia and 39 expected spot price change observations for each of the 17 subsets. Hence, the EEX sample consists of 663 baseload and 663 peakload basis, risk premia and expected spot price change observations. The NPX sample consists of 23 basis-, 23 premium- and 23 expected spot price change observations for each of the 17 subsets. The NPX sample size is 391 basis, premium and expected spot price change observations.

In the table below we provide the descriptive statistics of the basis, risk premia and expected spot price change observations for the EEX sample (table 5.10) and for the NPX sample (table 5.11).

	Baseload			Peakload		
	$S_T - S(t)$	$F_T(t) - S(t)$	$F_T(t) - S_T$	$S_T - S(t)$	$F_T(t) - S(t)$	$F_T(t) - S_T$
Mean	0.473	1.583	1.111	0.469	8.723	8.254
Std. Deviation	6.610	4.941	6.613	9.021	7.886	10.44
Number of observations: 663. Data is in €/MWh.						

Table 5.10: Descriptive statistics of daily EEX M1 price data

	$S_T - S(t)$	$F_T(t) - S(t)$	$F_T(t) - S_T$
Mean	1.506	10.86	9.353
Std. Deviation	25.05	23.14	26.83
Number of observations: 391. Data is in NOK/MWh.			

Table 5.11: Descriptive statistics of daily NPX M1 price data

From table 5.10, we see that the average basis and realized risk premia of peak load contracts are, as expected, higher for the peak load forwards relative to base load contracts. This stems from the fact that the variance of day-ahead prices in peak hours is higher. The standard deviation estimates reported in the table are of similar magnitude, which means that the equations (5.3) and (5.4) can reliably assign basis variation to either one, or a combination of the sources.
In table 5.11 we provide the descriptive statistics of the basis, risk premia and expected spot price change observations for the NPX sample.

5.4 Results

We will now present the main findings and the conclusions that can be drawn from these results.

5.4.1 Results for hypothesis 1: monthly sample

EEX

In order to examine whether forward prices incorporate information value of price forecasts and premia and how these fractions are affected by time to maturity, we split our EEX forward contract sample in six, according to the contracts maturity horizon.
In table 5.12 we provide the OLS estimation results of equation (5.3) and (5.4) regressed on the baseload contract data sets.

	M1	M2	M3	M4	M5	M6
α_0	0.176 (0.963)	0.304 (1.158)	0.496 (1.226)	0.940 (1.270)	1.419 (0.134)	1.686 (1.338)
β_0	0.391 (0.242)	0.444 (0.176)***	0.431 (0.148)***	0.470 (0.145)***	0.460 (0.135)***	0.490 (0.146)***
Adj. R^2_0	0.067	0.147	0.160	0.180	0.199	0.213
α_1	-0.176 (0.963)	-0.304 (1.158)	-0.496 (1.226)	-0.940 (1.270)	-1.419 (0.134)	-1.686 (1.338)
β_1	0.608 (0.244)***	0.556 (0.176)***	0.569 (0.148)***	0.530 (0.145)***	0.540 (0.135)***	0.509 (0.146)***
Adj. R^2_1	0.175	0.222	0.261	0.223	0.261	0.227
ADF	-4.970***	-4.472***	-4.317***	-4.181***	-3.884***	-3.810***
LB-Q	3.571 (0.059)	12.61 (0.000)	13.92 (0.000)	13.12 (0.000)	11.23 (0.001)	13.26 (0.000)

Newey-West Heteroskedasticity and Autocorrelation (HAC) robust standard errors are in parentheses. ***99%, **95%, *90% confidence level.
Augmented Dickey Fuller (ADF) tests statistic for θ_t and ω_t. Unit root rejected at ***99% confidence level, critical values: -3.617 (M1), -3.623 (M2), -3.629 (M3), -3.636 (M4), -3.642 (M5) and -3.650 (M6). Ljung Box Q-statistics (LB-Q) for the null hypothesis that there is no autocorrelation up to order k. Here k=1 and P-values are in parentheses.

Table 5.12: Ordinary Least Squares results Fama model for EEX baseload data

From table 5.12, we can observe that almost all β estimates are positive and significant at the 99% confidence level, which implies that the basis contains information about future spot price changes. Only the β_0 estimate of the next-month maturity contract is not significantly different from zero, which implies that the M1 basis incorporates no information value about future day-ahead price changes. We can see that respectively 39%, 44%, 43%, 47%, 46% and 49% of the basis observed M1-, M2-, M3-, M4-, M5- and M6 EEX baseload contracts account for future changes in the spot price. The percent of explanatory value of the basis to forecast the expected spot price change increases gradually with maturity. Because of the adding-up constraint of our joint-regression model, we see an opposite and declining pattern of the information value of forward prices to the expected risk premium with increasing time to maturity: the baseload M1 basis explains 61% of the variation in ex-post premia.
We see a declining trend in the size of the explanatory power of the basis about the risk premium to be realized in the delivery period for higher maturities (M1→ M6) up to 5.3%. The adjusted R^2 coefficients are in a range of 7% to 23% across all contract maturities, which suggest that the equations (5.3) and (5.4) provide a rather poor fit to the data. As discussed before, this is not uncommon for employing the Fama model to commodity futures data: see Fama and French (1987).
In table 5.12 the test statistics of the Augmented Dickey Fuller (ADF) test are reported, together with the critical values for testing at the 99% confidence level. This is a test statistic for the random walk hypothesis, which we employ on the residual processes θ_t and ω_t to guard against the possibility of interpreting misleading results, we must be sure that

the residual processes are no random walk. Evidence of a unit root implies that the residuals are non-stationary, henceforth this would imply we can not rely on the estimates provided. The ADF tests indicate that none of the residual processes of the maturity sample series are a random walk. The Ljung-Box Q-statistics at lag k is a test statistic for the null hypothesis that there is no autocorrelation up to order k. Under the null hypothesis it is asymptotically distributed as a Chi-square distribution with the degrees of freedom equal to the number of autocorrelations. From the LB-Q statistics reported in table 5.12 we conclude that the noise terms of the model equations (5.3) and (5.4) equations obtained for most maturity contract sample are autocorrelated, except for the M1 contract sample. Note that the standard errors are based on the estimator of the covariance matrix proposed by Newey and West (1987) and therefore controls for both serial correlation and heteroskedasticity.

In table 5.13 we provide the results of equation (5.3) and (5.4) estimated on the EEX peakload data. The results are slightly different from those reported for baseload contracts. From table 5.13 we can see that all β estimates are positive and significant at the 99% confidence level. This means that the basis contains significant information about both future spot price changes, as well as the risk premium to be realized in the delivery period. From the β_0 values, we conclude that respectively 26%, 31%, 33%, 39%, 39% and 42% of the basis observed M1-, M2-, M3-, M4-, M5- and M6 EEX peakload contracts reflect future changes in the spot price. The forecast power of the electricity futures contract increases with maturity. Because of the adding-up constraint of our joint-regression model, we find that the size of the explanatory value embedded in the futures basis about the expected risk premium decreases, when time-to-maturity increases. This pattern can be derived from the β_1 values reported in table 5.13.

Another interesting point worth noting is that when we compare the level of β_1 coefficients obtained from baseload data (table 5.12) with the level of β_1 peakload estimates, we can see note that the fraction that relates to the risk premium is higher in peakload contracts. This can be explained by the higher variance of day-ahead prices in those hours.

The ADF tests indicate that none of the residual processes of the maturity sample series are a random walk. From the LB-Q statistics reported in table 5.13 we conclude that the noise terms of the model equations (5.3) and (5.4) equations obtained for each maturity contract sample are autocorrelated, except for the M1 contract sample.

	M1	M2	M3	M4	M5	M6
α_0	-1.380 (1.700)	-1.731 (1.548)	-1.717 (1.516)	-1.738 (1.585)	-1.314 (1.560)	-1.365 (1.672)
β_0	0.256 (0.241)	0.313 (0.188)	0.326 (0.147)***	0.391 (0.131)***	0.392 (0.120)***	0.422 (0.122)***
Adj. R^2_0	0.025	0.086	0.113	0.153	0.179	0.191
α_1	1.380 (1.700)	1.731 (1.548)	1.717 (1.516)	1.738 (1.585)	1.314 (1.560)	1.365 (1.672)
β_1	0.744 (0.241)***	0.687 (0.188)***	0.674 (0.147)***	0.609 (0.131)***	0.608 (0.120)***	0.578 (0.122)***
Adj. R^2_1	0.289	0.357	0.390	0.323	0.362	0.320
ADF	-5.479***	-5.070***	-4.731***	-4.458***	-4.193***	-4.236***
LB-Q	3.407 (0.065)	10.28 (0.001)	18.25 (0.000)	11.27 (0.001)	9.354 (0.002)	11.82 (0.001)

Newey-West Heteroskedasticity and Autocorrelation (HAC) robust standard errors are in parentheses. ***99%, **95%, *90% confidence level.
Augmented Dickey Fuller (ADF) tests statistic for θ_t and ω_t. Unit root rejected at ***99% confidence level, critical values: -3.617 (M1), -3.623 (M2), -3.629 (M3), -3.636 (M4), -3.642 (M5) and -3.650 (M6). Ljung Box Q-statistics (LB-Q) for the null hypothesis that there is no autocorrelation up to order k. Here k=1 and P-values are in parentheses.

Table 5.13: Ordinary Least Squares results Fama model for EEX peakload data

In figure 5.2 we plot the β_0 and β_1 coefficients against the contract's time to maturity. We can clearly observe the downward slope of the β_1 values with time to maturity (see dotted line in figure 5.2). This means that the risk premium component incorporated in the basis of electricity futures contracts decreases with the time to maturity, which is consistent with the Samuelson effect. The results obtained from the EEX market confirm our hypothesis (H1) that the risk premium embedded in electricity forward contracts decreases with time to maturity.

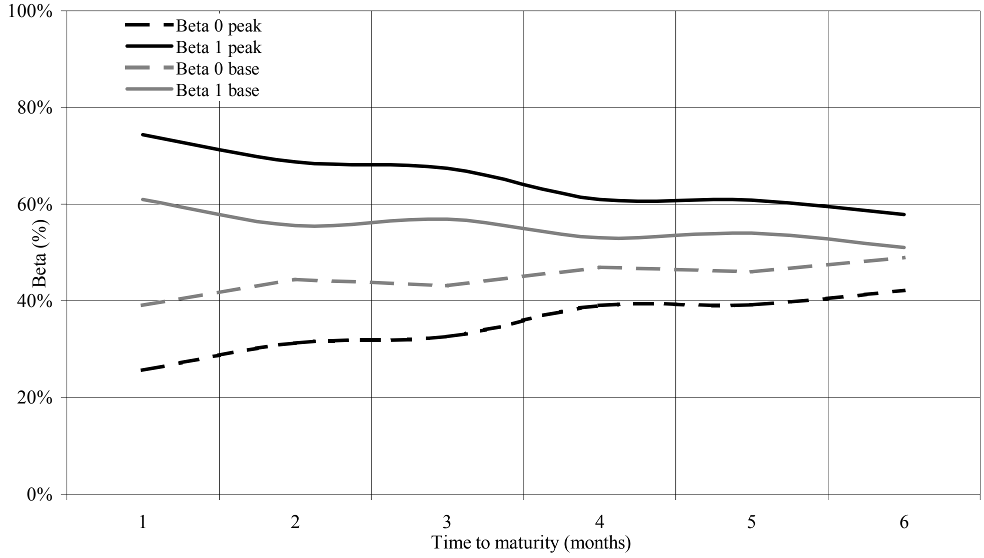


Figure 5.2: Monthly spot price forecast- and risk premia results for EEX futures curve

APX/ENDEX

In table 5.14 we provide the OLS estimation results of joint-regression test for the APX/ENDEX baseload and peakload data. Before examining the β-estimates that we are primarily interested in, it is worth considering ADF-test results first. These statistics are in a range of –1.35 and –2.96, and are higher than the critical values that are in a range of –2.97 and –2.99. We therefore cannot reject the null hypothesis that the error terms in model (5.3) and model (5.4) follow a random walk. Hence, the results obtained for these contract maturities are misleading results. Desk research at the Dutch power market learns us that two incidents in the second half of 2003 have caused extreme price shocks, which might drive the above-discussed erroneous results. The first event takes place in on 10 August 2003. On that day, the Dutch government issues a red alert code that implied that power generators weren't allowed to use river water for cooling purposes[48]. This resulted in baseload prices of Euro €660.3 p/MWh on 11 August, €368.8 p/MWh on 12 August and €637.4 p/MWh on 13 August. The average baseload price in August 2003 is €83.98/MWh, and amounts €117.0/MWh for peakload delivery. Note that this monthly average price is used as a proxy for S_T in equation (5.3).

[48] The Dutch production park mainly consists of coal and gas generators, which need river water for cooling purposes. Since the river temperature the weeks preceding 10 August reached the critical temperature of 23 degrees Celcius due to a very hot second half of July 2003, it was expected that cooling water that was used by the generators and brought back into the river would lead to river temperatures that would exceed the critical level of 30 degrees Celsius. Hence this would damage the river's ecological system. The previous time a code red was issued was in 1995.

The second extreme price event is the spot price quote on the first trading day of the month in November 2003; on 3 November 2003 the baseload price is €122.6/MWh, and the peakload price is equal to €177.3/MWh. These prices are clearly outliers, when we consider the descriptive statistics of both the baseload and peakload price distribution.[49] We have performed an outlier test, of which the results are given in the Appendix (See A5.4-A5.7). Based on these results, we conclude that these outliers drive the results presented in table 5.14 (See Appendix for discussion).

	Baseload			Peakload		
	M1	M2	M3	M1	M2	M3
α_0	8.067 (4.243)*	-0.349 (4.039)	0.714 (4.143)	-2.695 (7.153)	-9.329 (7.551)	-9.903 (5.833)
β_0	1.143 (0.130)***	0.873 (0.245)***	1.056 (0.130)***	1.122 (0.145)***	0.845 (0.259)***	1.097 (0.144)***
Adj. R^2_0	0.756	0.599	0.669	0.756	0.562	0.683
α_1	-8.067 (4.243)*	0.349 (4.039)	-0.714 (4.143)	2.695 (7.153)	9.329 (7.551)	9.903 (5.833)
β_1	-0.143 (0.130)	0.127 (0.245)	-0.056 (0.130)	-0.122 (0.145)	0.155 (0.259)	-0.097 (0.144)
Adj. R^2_1	0.012	0.000	-0.032	0.000	0.008	-0.022
ADF	-1.480	-3.224**	-1.812	-1.354	-2.957	-2.733
LB-Q	0.000 (0.979)	3.931 (0.047)	5.168 (0.023)	0.068 (0.579)	3.851 (0.050)	5.709 (0.017)

Newey-West Heteroskedasticity and Autocorrelation (HAC) robust standard errors are in parentheses. ***99%, **95%, *90% confidence level.
Augmented Dickey Fuller (ADF) tests statistic for θ_t and ω_t. Unit root rejected at ***99% confidence level, critical values: -3.689 (M1); -3.738 (M2);-3.711 (M3).
Unit root rejected at **95% confidence level, critical values: -2.972 (M1); -2.975 (M2); -2.981 (M3). Ljung Box Q-statistics (LB-Q) for the null hypothesis that there is no autocorrelation up to order k. Here k=1 and P-values are in parentheses.

Table 5.14: Ordinary Least Squares results Fama model for APX/ENDEX data

Re-estimation model

We exclude the two extreme price differential observations from our M1, M2 and M3 sample, and re-estimate the model (5.3) and (5.4). The results are provided in table 5.15. From table 5.15 we can see that all β_0 estimates are positive and significant at the 99% confidence level.

[49] The mean, standard deviation and maximum value of the baseload forward price series, are respectively equal to 38.81, 20.31 and 122.6. For the peakload forward price series these descriptive statistics have values of respectively 48.55, 29.74 and 177.3.

	Baseload			Peakload		
	M1	M2	M3	M1	M2	M3
α_0	-1.380 (1.701)	-1.002 (2.093)	0.393 (2.394)	-7.396 (2.747)*	-7.838 (3.181)**	-7.502 (3.495)**
β_0	0.697 (0.143)***	0.884 (0.224)***	0.796 (0.189)***	0.587 (0.169)***	0.743 (0.230)***	0.798 (0.242)***
Adj. R^2_0	0.499	0.490	0.493	0.426	0.422	0.499
α_1	1.380 (1.701)	1.002 (2.093)	-0.393 (2.394)	7.396 (2.747)**	7.838 (3.181)**	7.502 (3.495)**
β_1	0.303 (0.143)***	0.116 (0.224)	0.204 (0.189)	0.412 (0.169)***	0.257 (0.230)	0.202 (0.242)
Adj. R^2_1	0.126	-0.022	0.021	0.257	0.051	0.021
ADF	-4.589***	-3.003**	-3.200**	-4.888***	-3.386**	-3.132**
LB-Q	0.074 (0.795)	6.196 (0.013)	6.570 (0.010)	0.003 (0.973)	3.827 (0.050)	5.691 (0.017)

Number of observations for each individual regression is 28 (for M1), 27 (for M2) and 26 (for M3). Newey-West Heteroskedasticity and Autocorrelation (HAC) robust standard errors are in parentheses. ***99%, **95%, *90% confidence level.
Augmented Dickey Fuller (ADF) tests statistic for θ_t and ω_t. Unit root rejected at ***99% confidence level, critical values: -3.699 (M1); -3.738 (M2);-3.711 (M3).
Unit root rejected at **95% confidence level, critical values: -2.976 (M1); -2.992 (M2); -2.981 (M3) Ljung Box Q-statistics (LB-Q) for the null hypothesis that there is no autocorrelation up to order k. Here k=1 and P-values are in parentheses.

Table 5.15: Ordinary Least Squares results Fama model for APX/ENDEX outlier-free data

This implies that the basis incorporates information about changes in future prices observed at the day-ahead markets. In particular, we observe that the baseload basis for M1, M2 and M3 contracts captures respectively 69.7%, 88.4% and 79.6% of the expected day-ahead price change.
The percentages are somewhat lower for the peakload basis: 58.7% (for M1), 74.3% (for M2) and 79.8% (M3). This result is consistent with the empirical findings reported for the EEX market (see table 5.12 and 5.13). As can be seen from the table, the β_1 coefficients are not significantly different from zero, except for the estimate derived from both the M1 baseload and M1 peakload data.

From the ADF statistics listed in table 5.15, we observe that the model residuals, which we obtain from estimating the joint regression equations on the individual contract maturities, follow a stationary process. In particular, we see that the values of the ADF test statistics for all three maturities are lower than the ADF critical values at the 95% and/or 99% confidence level. Hence, the removal of outliers from the sample has yielded results that can be interpreted meaningfully. From the LB-Q statistics reported in table 5.15 we conclude that the noise terms of the model equations (5.3) and (5.4) equations obtained for each maturity contract sample are autocorrelated, except for the M1 contract sample.

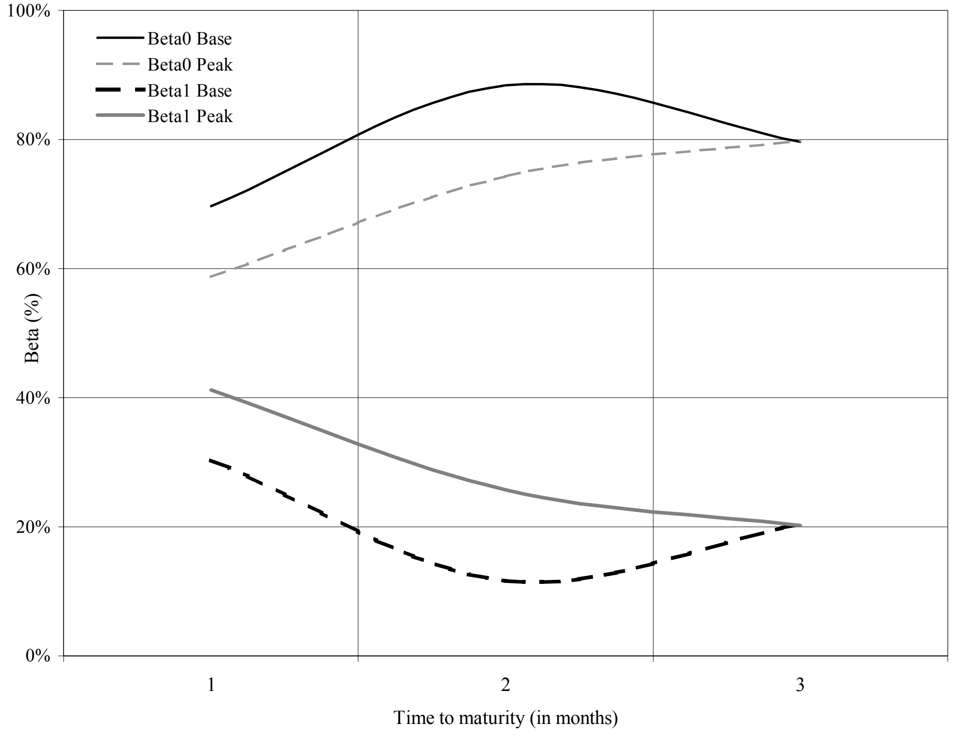


Figure 5.3: Monthly spot price forecast (β_0) and risk premium (β_1) outcomes for APX/ENDEX forward curve

In figure 5.3 we display the spot price forecast and risk premium pattern over the ENDEX baseload and peakload forward curve, by plotting the β_0 and β_1 percent values against the time to maturity. As we can see from figure 5.3, the relationship between the explanatory value of the basis relative to spot price forecasts (and expected risk premia) is curvilinear increasing (decreasing) with time to maturity. Although the results obtained from the Dutch market reflect the time-to-maturity pattern over three contract maturities only, we can conclude that the evidences provides at least a degree of support that the risk premia incorporated in forward prices shows a downward trend over the time to maturity of the contract. We therefore conclude that hypothesis 1 is supported.

5.4.2 Results for hypothesis 2: daily sample

We now report the model (5.3) and (5.4) outcomes estimated on the daily EEX and NPX sample. We only provide the values and standard errors of the β_0 and β_1 estimates, since these are the only explanatory variables in equation (5.3) and (5.4) that potentially embed information value over the spot price changes and risk premia in forward- and future prices.

EEX

Note that the estimates reported in the top row of table 5.16 are also in table 5.12, which makes sense as these results are derived from estimating the Fama model on the same dataset: EEX next-month (M1) delivery baseload price data observed on the first-trading-day-of-the-month (n=1).

From table 5.16 we can furthermore see that as from the beginning of the month that the derivative exchange quotes M1 future prices (n = 1 to 5), the value of the β_0 is not significantly different from zero. Hence, we conclude that there is no evidence of a forecast component that embeds information about the future day-ahead price change in the M1 basis. When we move closer to the expiration date (n= 6 → expiration), we see that the value of the β_0 parameter becomes significantly different from zero, and interestingly shows an increasing trend. Apparently, the basis of M1 baseload contracts only incorporates information value over the expected spot prices when we roll closer to the expiration day. In particular, we see that the basis fraction observed at the 6^{th} trading day of the month that represents the power to forecast spot price changes equals 40%, and this percentage steeply increases in the subsequent trading days and eventually stabilises to a level of 60% on the 17^{th} trading day of the month. Note that a percentage of 100% would imply that the forward price is an unbiased predictor of the spot price.

The β_1 values reported in table 5.16, are all significantly different from zero at the 99% confidence level. We see an initially increasing trend in the size of the risk premium component embedded in the M1 basis observed at the first trading days of the month (n=1 to 5). But when we move closer to maturity, we observe that the basis fraction observed at the 6^{th} trading day of the month that reflects the variation in the to be realized risk premium equals 60%, and this percentage decreases in the next trading days to a level of 40% a few days before expiration. We now perform the Augmented Dickey Fuller (ADF) to test for the existence for a unit-root in the disturbance terms. Evidence of a unit root implies that the residuals are non-stationary, henceforth the estimation results are worthless (spurious regression). The critical value of this test is -3.753 (99% confidence level). The ADF statistics that we find for all of the 17 individual regressions are well below the critical value of -3.620. We therefore conclude that the residual processes θ_t and ω_t are stationary, which means that the results presented in table 5.16 are not subject to spurious interpretation.

n	β_0	Adj. R^2_0	β_1	Adj. R^2_1	ADF
1	0.391 (0.244)	0.067	0.609 (0.244)***	0.175	-4.159***
2	0.343 (0.299)	0.039	0.657 (0.299)***	0.178	-4.338***
3	0.356 (0.276)	0.051	0.644 (0.276)***	0.191	-4.568***
4	0.231 (0.261)	0.004	0.769 (0.261)***	0.234	-4.687***
5	0.271 (0.829)	0.020	0.729 (0.214)***	0.238	-4.871***
6	0.403 (0.105)***	0.124	0.597 (0.105)***	0.255	-4.421***
7	0.394 (0.173)***	0.059	0.606 (0.173)***	0.157	-5.036***
8	0.499 (0.141)	0.104	0.500 (0.141)***	0.105	-4.948***
9	0.579 (0.116)***	0.148	0.421 (0.116)***	0.074	-4.921***
10	0.626 (0.110)***	0.180	0.374 (0.110)***	0.058	-4.696***
11	0.663 (0.104)***	0.210	0.337 (0.104)***	0.047	-4.769***
12	0.689 (0.117)***	0.232	0.311 (0.117)***	0.039	-4.725***
13	0.635 (0.126)***	0.184	0.365 (0.126)***	0.054	-5.085***
14	0.662 (0.147)***	0.196	0.338 (0.147)**	0.042	-4.775***
15	0.643 (0.157)***	0.172	0.357 (0.157)**	0.044	-4.772***
16	0.609 (0.202)***	0.150	0.391 (0.202)*	0.054	-4.877***
17	0.603 (0.150)***	0.179	0.397 (0.150)**	0.074	-4.822***

N: Nth trading day of the month. Number of observations for each individual regression is 39.
Newey-West heteroskedasticity and autocorrelation consistent standard errors are in parentheses. ***99%, **95%, *90% confidence level.
Augmented Dickey Fuller (ADF) test: Unit root rejected at ***99% confidence level (critical value: -3.620)

Table 5.16: Ordinary Least Squares results Fama model for daily EEX baseload data

In table 5.17 we provide the peakload results. As can be seen from the table, the β estimates for the EEX peakload contracts show a similar pattern as we have reported for the baseload contracts, but results are slightly different. Compared to the baseload results, we observe that the fraction that relates to the risk premium is higher in peakload contracts throughout all trading days of the month. This can be explained by the higher variance of spot prices in those hours. Again we see an initially upward pattern (from 74% on the 1st trading day to 101% on the 5th trading day) followed by a strong declining pattern in the risk premium level in the subsequent five trading days; from 84% on the 6th trading day to 45% on the 12th trading day.

N	β_0	Adj. R^2_0	β_1	Adj. R^2_1	ADF
1	0.256 (0.241)	0.025	0.744 (0.241)***	0.289	-5.479***
2	0.183 (0.298)	-0.004	0.817 (0.298)***	0.299	-5.680***
3	0.155 (0.287)	-0.007	0.845 (0.287)***	0.348	-5.733***
4	-0.041 (0.263)	-0.026	1.040 (0.263)***	0.464	-6.405***
5	-0.016 (0.227)	-0.027	1.016 (0.227)***	0.493	-6.471***
6	0.156 (0.194)	0.003	0.844 (0.194)***	0.455	-4.857***
7	0.068 (0.268)	-0.023	0.932 (0.268)***	0.387	-5.929***
8	0.277 (0.198)	0.022	0.723 (0.198)***	0.235	-5.480***
9	0.369 (0.163)**	0.058	0.631 (0.163)***	0.187	-5.411***
10	0.455 (0.158)***	0.106	0.545 (0.158)***	0.153	-5.097***
11	0.510 (0.133)***	0.141	0.490 (0.133)***	0.130	-5.140***
12	0.552 (0.141)***	0.175	0.448 (0.141)***	0.115	-5.030***
13	0.496 (0.149)***	0.137	0.504 (0.149)***	0.142	-5.287***
14	0.530 (0.180)***	0.159	0.470 (0.180)**	0.126	-5.092***
15	0.436 (0.190)**	0.096	0.564 (0.190)***	0.164	-5.312***
16	0.433 (0.229)	0.064	0.567 (0.229)***	0.243	-5.611***
17	0.430 (0.179)*	0.087	0.570 (0.179)***	0.302	-3.959***

N: N^{th} trading day of the month. Number of observations for each individual regression is 39.
Newey-West heteroskedasticity and autocorrelation consistent standard errors are in parentheses. ***99%, **95%, *90% confidence level.
Augmented Dickey Fuller (ADF) test: Unit root rejected at ***99% confidence level (critical value: -3.620)

Table 5.17: Ordinary Least Squares results Fama model for daily EEX peakload data

The risk premium fraction embedded in the future price, then stabilizes around 57% close to expiration of the contract. From the ADF test that we perform on the the residual processes θ_t and ω_t of all 17 regressions, we conclude that the estimation results provided in table 5.17 are not subject to spurious interpretation.
In figure 5.4 we display the β_0 slope coefficients reported in table 5.16 and 5.17 against the trading days of the month N. Evidence that β_0 is positive means that the basis embeds power to forecast future day-ahead price changes.

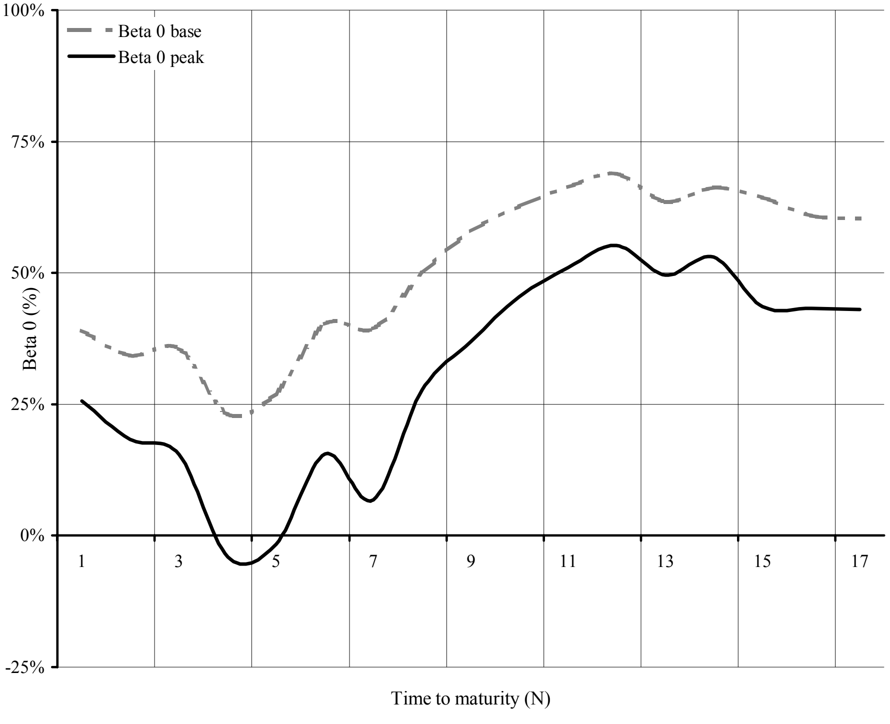


Figure 5.4: Price forecast results for EEX M1 contracts

From figure 5.4 we can observe the upward slope in the β_0 value when we move from the first trading day of the month to the expiration date. The fraction of the future prices incorporated in the baseload (peakload) basis eventually stabilizes around a level of 60% (40%). Hence, the futures price does not perfectly converge to the day-ahead price. Also the risk premium fraction does not completely evaporates out of the futures price. However, we can observe an upward sloping convergence pattern. A point worth emphasizing is that because the delivery of electricity under month-ahead contracts is uniformly spread over the month (1 MWh in each baseload or peakload hour), the holder of the forward / futures contract is exposed to the differential between the forward / futures price and the average of the day-ahead prices inside the delivery period. Therefore the electricity derivative price may not exactly converge to the day-ahead price, henceforth the convergence assumption is valid only on average.

NPX

In table 5.18 the equation (5.3) and (5.4) outcomes are given for the NPX data.

From table 5.18, we conclude that the M1 base load contracts traded on the NPX clearly show a convergence of forward prices to spot price expectations when maturity is approached; on the first trading day the spot price expectation is not significantly different from zero but gradually increases from a basis fraction equal to 26% on the 7th trading day up 77% on the 17th trading day. The β_1 values reported in table 5.17, are all significant at the 99% confidence level. We see an initially increasing trend in the size of the risk premium component embedded in the M1 basis observed at the first trading days of the month (n=1 to 5). But when we move closer to maturity, we observe that the basis fraction observed at the 6th trading day of the month that represents information value about the expected risk premium embedded in the forward basis equals 78%, and this percentage is gradually decreases when we roll closer to the expiration date up to a level of 24%. We employ the ADF test on the noise terms θ_t and ω_t in the Fama model (5.3) and (5.4).

N	β_0	Adj. R^2_0	B_1	Adj. R^2_1	ADF
1	0.177 (0.266)	0.025	0.823 (0.266)***	0.296	-3.672**
2	0.244 (0.244)	0.014	0.756 (0.244)***	0.271	-3.548**
3	0.290 (0.230)	0.026	0.710 (0.230)***	0.244	-3.594**
4	0.188 (0.237)	0.113	0.812 (0.237)***	0.330	-3.703**
5	0.109 (0.237)	0.159	0.891 (0.237)***	0.320	-3.881***
6	0.218 (0.223)	0.142	0.782 (0.223)***	0.334	-3.820***
7	0.262 (0.173)*	0.108	0.738 (0.173)***	0.365	-3.935***
8	0.306 (0.156)**	0.046	0.694 (0.156)***	0.346	-3.993***
9	0.307 (0.145)*	0.007	0.693 (0.145)***	0.326	-4.171***
10	0.361 (0.134)**	-0.002	0.639 (0.134)***	0.298	-4.302***
11	0.413 (0.128)**	-0.020	0.587 (0.128)***	0.287	-4.323***
12	0.432 (0.126)**	-0.030	0.568 (0.126)***	0.266	-4.478***
13	0.454 (0.144)**	-0.019	0.546 (0.144)***	0.259	-4.768***
14	0.594 (0.169)***	-0.010	0.406 (0.169)**	0.108	-4.717***
15	0.599 (0.179)***	-0.009	0.401 (0.179)*	0.101	-4.935***
16	0.797 (0.201)***	-0.003	0.203 (0.174)	-0.012	-4.549***
17	0.765 (0.150)***	-0.006	0.235 (0.150)	0.013	-4.627***

N: Nth trading day of the month. Number of observations for each individual regression is 29.
Newey-West heteroskedasticity and autocorrelation consistent standard errors are in parentheses. ***99%, **95%, *90% conf. level.
Augmented Dickey Fuller (ADF) test: Unit root rejected at ***99% (critical value: -3.770) confidence level, **95% confidence level (critical values: -3.005).

Table 5.18: Ordinary Least Squares results Fama model for daily NPX data

For all of the 17 individual regressions, we find ADF statistics that are well below the critical value of -3.005. We conclude that the estimation results provided in table 5.17 are not subject to spurious interpretation. In figure 5.5 we delineate the β_0 slope coefficients against the trading days of the month N.

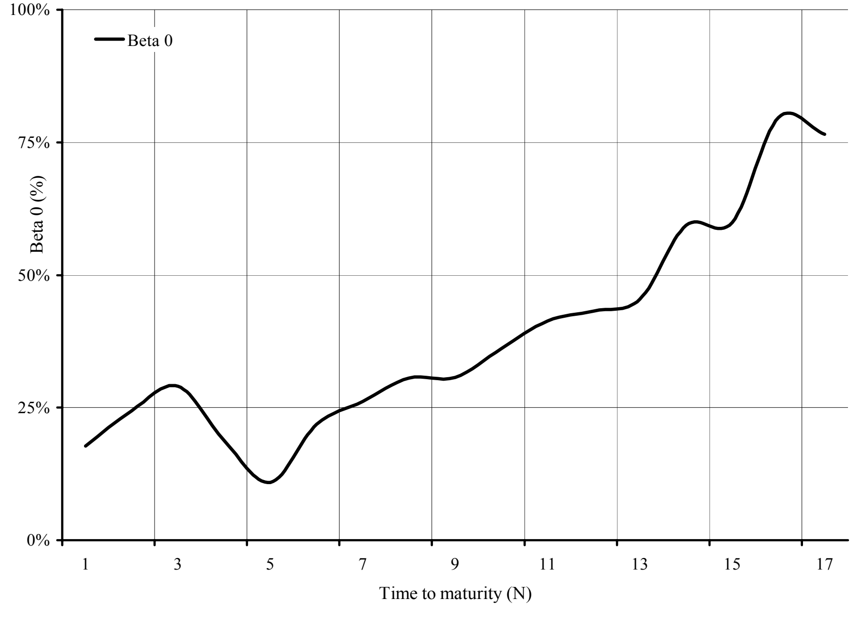


Figure 5.5: Price forecast results for NPX M1 contracts

From figure 5.5, we can clearly observe the upward slope of the β_0 values when we roll (from one trading day to the next) to the expiration date. There is a degree of price convergence to expected spot prices observable in the NPX market. The pattern depicted in above diagram is even more convincing evidence in support of the spot price convergence of electricity forward prices, as observed in the EEX market (compare figure 5.4 with figure 5.5). The reported evidence is consistent with the classical derivative pricing theory: the derivative price converges to the spot price of the underlying asset and eventually approximates the spot price close when the delivery period is reached (Hull, 2002).

We have provided empirical evidence from two of the most active derivative exchanges in the world that electricity derivative prices have explanatory power to forecast future price changes. Furthermore we show that this fraction incorporated in the basis of the derivative shows an upward slope when we roll to the expiration date of the contract. As expected, we do not report evidence consistent with perfect price convergence. However, these results provide evidence that there is a degree of derivative price convergence[50] to expected spot prices in electricity markets. Based on the provided empirical evidence obtained from two international electricity derivative markets, we conclude that hypothesis 2 is supported.

5.5 Concluding remarks

Electricity derivative prices exhibit significant information about risk premiums and expected changes in forward prices on the day-ahead markets. From monthly electricity forward prices of contracts with a time-to-maturity ranging from six-months up to one-month, we disclose that the size of these components changes in a way that is consistent with commodity derivative price theory (Samuelson effect), when the contracts rolls to the expiration date as close as one month. This time-to-maturity pattern that has been documented for many commodity prices other than electricity forward prices, can be explained by mean-reverting behavior of the underlying spot process. Far from maturity, the chance that a spot price will revert back to its long-term mean will be high, but this chance decreases when we roll from derivative contracts with a long time-to-maturity to a shorter maturity horizon. To compensate for the rise in price volatility when the contract rolls closer to her expiration date, the investors in the forward contract expect a higher risk premium. We also study the time-to-maturity effect for one month-ahead contracts, when we roll from one trading day to the next up to a few trading days before expiration. We disclose that the fractions of the premium and forecast component change in a way that is consistent with the theory that forward prices converge to its underlying spot price very close to expiration. This is an important finding because the standard assumption in derivative pricing theory is that the threat of arbitrage keeps the spot price and future price in line with each other. Because the non-storability of electricity means that the no-arbitrage condition cannot be applied to link spot and forward prices, it is interesting to report evidence that suggests that forward prices and spot prices are linked together in a way that goes in line with it. The documented results might give traders and risk managers insight in the risk premiums and might help to assess price expectations when they evaluate the forward price curve. One typical application of our result is setting mean price levels in simulation models that produce potential price patterns for future time periods.

5.6 Appendix

Risk premium and maturity relationship

The forward/futures pricing model that Lucia and Schwartz (2002) propose reads as:

$$F_T(t) = E_0^*(S_T) = f(T) + X_0 e^{-kT} + [\alpha^*(1-e^{-kT})] \qquad \text{(A.5.1)}$$

From equation (A.5.1), we can see that the expected spot price in T, under the risk neutral probability measure, noted as $E_0^*(S_T)$, is equal to the sum of a deterministic process f(T), a stochastic process $X_0 e^{-kT}$ term, and a component that can be looked upon as a risk premium term, $RP_T(t)$, noted in square brackets. Thus:

$$RP_T(t) = \alpha^*(1-e^{-kT}), \text{ where } \alpha^* = -\lambda\sigma/\kappa. \qquad \text{(A.5.2)}$$

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50 As discussed in section 5.2, according to classicical derivative pricing theory, the derivative price converges to the spot price of the underlying asset and eventually approximates the spot price close when the delivery period is reached.

λ is the market price per unit risk, κ is the mean-reverting rate and σ represents the spot price volatility. Since the values of these Greeks are all positive, the term in square brackets is decreasing in T. Introducing Δ as the differencing operator, we can write the first-order derivative of RP_T as:

$$\Delta RP_T/\Delta T = -\lambda\sigma e^{-kT} \qquad \text{(A.5.3)}$$

From equation (A.5.3), we conclude that the risk premium decreases with time to maturity.

Outlier test

- The average baseload (peakload) price in August 2003 is €83.98/MWh (€117.0/MWh).
- The baseload (peakload) price on 3 Nov. 2003 is €122.6/MWh (€177.3/MWh (peakload).

We introduce the dummy Daug that equals 1 in the month August 2003, and 0 in the other months. We introduce the dummy Dnov that equals 1 in the month November 2003, and 0 in the other months. Then (5.3) and (5.4) becomes:

$$S_T - S(t) = \alpha_0 + \beta_0 (F_T(t) - S(t)) + \gamma_0 Daug + \delta_0 Dnov + \sigma_0 \theta_t, \text{ where } \theta_t \sim IID(0, 1) \qquad \text{(A.5.4)}$$

$$F_T(t) - S_T = \alpha_1 + \beta_1 (F_T(t) - S(t)) + \gamma_1 Daug + \delta_1 Dnov + \sigma_1 \omega_t, \text{ where } \omega_t \sim IID(0, 1) \qquad \text{(A.5.5)}$$

The estimation results are listed in table A5.6 (baseload data) and A5.7 (peakload data):

α_0	β_0	γ_0	δ_0
-0.428	0.789	45.82	-28.97
(1.257)	(0.104)***	(3.016)***	(7.486)***
α_1	β_1	γ_1	δ_1
0.428	0.211	-45.82	28.97
(1.257)	(0.104)**	(3.016)***	(7.486)***

Table A5.6: ENDEX baseload data

α_0	β_0	γ_0	δ_0
-3.587***	0.652	63.12	-44.50
(1.013)	(0.096)***	(3.016)***	(7.062)***
α_1	β_1	γ_1	δ_1
3.587***	0.348	-63.12	44.50
(1.013)	(0.096)**	(3.016)***	(7.062)***

Table A5.7: ENDEX peakload data

From table A5.6 and table A5.7, we can see that the coefficients γ and δ are significant at the 99% confidence level. Hence, the extreme price events observed in August 2003 and November 2003 influence the dependent variables in equation A5.4 and A5.5, being respectively the expected spot price change ($S_T - S(t)$) and the expected risk premium ($F_t(T) - S_T$).

Chapter 6: Electricity Portfolio management[51]

6.1 Introduction

The worldwide liberalisation process in the energy markets has generated serious risk in the price of electricity products. As a result of the liberalization trajectory, risk has been transferred through the industry chain from the supply side to the end-user. The energy world of the end-user changed dramatically. She cannot rely anymore on one regulated power price (that hardly changed) for their consumption. The economic law of supply and demand requires that she has to act (e.g. change from supplier), in order to exploit the lowest price or best service offered by suppliers on the market. Also, market places have been created on which market participants can trade electricity forward contracts for different delivery periods. Hence, besides choosing the supplier that provides in her needs, the end-user also needs to think about what purchasing strategy for delivery of power (on spot or in future) she prefers. Hence, this strategy is chosen in such a way that her future consumption is met by a combination of spot- and forward contracts, which *matches* her risk preference. A typical purchasing strategy, commonly referred to as a tender strategy, among end-users is to buy ones a year (or a few times a percentage of) the annual consumption for the next calendar year forward. Obviously a tender strategy is profitable when the end-user is able to time the moment of purchase in such a way that it turns out to be the minimum cost strategy. But this is wisdom with hindsight. The question that is relevant is how the end-user can select her portfolio out of the many strategies (the tender-strategy is just one of them), that matches her risk appetite.

In this Chapter we are interested whether the portfolio theory proposed by Markowitz (1952) can be applied to electricity markets. This conceptual framework allows an investor to select the portfolio that matches her risk appetite, and has been widely applied to portfolios consisting of a wide range of assets (e.g. stocks, bonds, exchange rates, commodities and so forth). Interestingly, various empirical studies have concentrated on the Markowitz framework in other recently deregulated industries (pension industry) that have seen a similar risk-transfer as described above: e.g. Boyle et al (2006) study the portfolio selection problem of employees regarding contribution pension plans. But so far, this has not been done in electricity markets. It is therefore interesting to shed light on the applicability of the Markowitz (1952) framework in electricity markets, since it enables the end-user to derive her optimal purchasing strategy. We do this for a static[52] two-asset electricity portfolio problem: The end-user can hedge her portfolio cost risk over a combination of day-ahead and one-month ahead forward contracts. Finding optimal hedge ratios for the position different contract maturities (day-ahead and one-month ahead), is evidence that the Markowitz framework structures the sourcing.

[51] This Chapter is based on: R. Huisman, and C. Huurman (2006), "Electricity purchasing strategies: Applying portfolio theory in power markets" *Working paper RSM Erasmus University*. We thank participants of Energyforum conference in Rotterdam (10-11 May 2006) for valuable comments.

[52] Static means that once the hedge ratio is decided, it cannot be changed.

Although academic research on portfolio selection models is well-established and includes classical works of Ederington (1979) and Stulz (1984)[53], these models cannot be directly applied to electricity markets. This is due to electricity price- and load dynamics. Only a very few studies have addressed the static portfolio selection problem in electricity markets. Fleten et. al (2000) use a 256 scenario model to solve the portfolio selection problem of a hydro power producer who allocates production uncertainty (that stems from inflow to reservoirs) over a combination of electricity day-ahead and forward contracts. Vehviläinen and Keppo (2003) convert the stochastic utility portfolio problem (for producers and end-users) set in continuous time, into a deterministic non-linear programming problem. This two-step methodology is proposed because there are no analytical formulas for electricity derivatives due to the complex spot price process and they therefore rely on numerical approximation. Vehviläinen and Keppo claim that the Monte Carlo method is superior to a Markowitz approach, but they don't provide evidence to support that. In fact, they solve the portfolio selection problem in a basic setting (although they claim that their method is capable of identifying the optimal combination for complex power portfolios), similar to ours.[54]
In this study we use data obtained from the Dutch power market. From the national transmission system operator TenneT (See Chapter 2, for a discussion on TenneT), we obtain load schemes from industrial end-users. From the Amsterdam Power Exchange (APX) we derive hourly day-ahead prices, and from the European Energy Derivatives Exchange (ENDEX) we get next-month (M1) forward prices. We extend the empirical literature by showing that the Markowitz framework, with some proper modifications, can be meaningfully applied for optimal portfolio selection in electricity markets. Our proposed method provides a framework for mapping the risk appetite to market contracts, and constitutes a first step for formulating a strategic benchmark for portfolio holders who wish to manage the sourcing mix over a certain time horizon.

The remainder of this Chapter is structured as follows. Section 6.2 describes mean-variance portfolio theory and safety-first models, and derives the mean-variance equations needed to solve the portfolio optimization problem. Section 6.3 discusses the data used in this study. Section 6.4 conducts the empirical analysis. Section 6.5 concludes.

6.2 Portfolio theory in electricity markets: Markowitz and beyond

In this section we discuss the Markowitz portfolio theory, and additions to his model that have been proposed since he published his work in 1952. Markowitz introduced mean and variance as meaningful measures of the expected return and risk[55] of a portfolio that is held by an investor who prefers more over less, and is risk averse. The investor is assumed to be

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[53] Ederington uses a basic portfolio model to hedge the foreign exchange risk exposure of a financial security portfolio. Stulz (1984) does essentially the same, only considers a stochastic underlying asset position.

[54] Vehviläinen and Keppo (2003) obtain the weekly expected prices of the spot price forecast from fitting a smooth curve continuously through the NPX forward quotes for the period 1996 to 2000. Here they assume that the expected spot price equals the forward price, hence the existence of nonzero risk premium in the forward price is ignored.

[55] Risk can be defined as the volatility of unexpected outcomes. It is best measured in terms of probability distribution functions (Jorion, 1997). Earlier academic works on expectations and probability theory date back as far as the 16th century.

mean-variance optimizer. Hence, that when two portfolios have the same expected outcome, she chooses the portfolio with the lowest risk. Or alternatively, she would choose the portfolio with the highest expected return (or lowest expected costs), when the choice is between two portfolios that are exposed to the same amount of risk. Other assumptions are that the investors' utility functions are quadratic and returns are normally distributed (For an excellent overview of mean-variance portfolio theory, see Elton et al. (2003)). Markowitz defined standard deviation[56] as the appropriate risk measure for portfolio selection. The above-defined mean-variance framework has been the standard in the financial industry ever since.
Roy (1952) introduces an alternative methodology (that circumvents the cumbersome expected utility calculations in Markowitz (1952)). Roy advocates the criterion that the optimal portfolio is the portfolio that has the smallest probability of producing a return below a prespecified level. Hence, this approach concentrates on the returns below the mean, while the standard deviation measures the possibility of returns below *and* above the mean. Roy's downside risk criterion appeals to the investor's true interpretation of risk. The well-known Value-at-risk (VaR) methodology, which has become the standard risk measure in the banking world as of the 1980s[57], stems from Roy's downside risk methodology. VaR tells the investor that he can be x% confident that his loss will not exceed VaR over a pre-specified period. Hence, the investor can set the confidence level (x%) and time horizon, and this method translates the portfolio risk to a single number (amount of money), being the VaR. Campbell et. al (2001) build on Roy's safety first theorem, and empirically test a framework for selection of a portfolio consisting of two risky assets (stocks and bonds), using a VaR constraint that allows for incorporating non-normal properties of the portfolio's return distribution.
Many financial series such as stock returns, exchange rates (but also power prices, as we have seen in Chapter 3) namely exhibit properties such as tail fatness or skewness and in these cases the standard deviation is an inadequate risk measure. However, the benefits of applying VaR should not be overestimated. Bawa (1975) has shown that when a distribution that is given by it's expectation and standard deviation, ranking portfolios by VaR will lead to the same optimal portfolio as ordering portfolios by the standard deviation. VaR can be considered (in these cases) as a multiple of the standard deviation. Hence, the additional information that is provided by applying VaR should always be carefully examined. We therefore view the above discussed approaches merely as insightful additions to the traditional conceptual framework proposed by Markowitz.

As mentioned in the previous section, when mean-variance portfolio theory is applied to solve the optimization problem for a portfolio consisting of financial assets, the solution space is a return-risk space. Since electricity is a non-storable 'asset', the concept of returns cannot be meaningfully applied. We therefore have to analyse our portfolio

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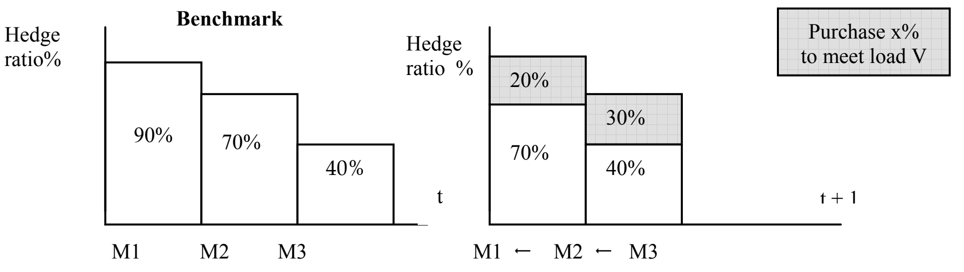
[56] Variance, calculated as the square of the standard deviation, introduced by Fisher (1918).
[57] Value-at-Risk is the widely accepted downside risk measure for financial institutions, and is that popular because the advantage of quantifying the portfolio risk by VaR is that you have a single number/amount of money, VaR limit, that measures the total risk in the institution's portfolio of financial assets. The VaR level that is recommended by the Basle Committee for Banking Regulation, tells us that the maximum loss incurred over a pre-specified period, should only exceed VaR once every hundred (1%) cases.

problem in a profit-risk space, or alternatively a cost-risk space, instead. We choose for a cost-risk space because we do not want to make any assumptions about the sales price / or profit margin corresponding to a portfolio that is needed to derive the portfolios profit (defined as the difference between sales and costs). Studies that concentrate on selecting optimal purchasing strategies through applying mean-variance analysis, date back as far as the 1970s. Most studies in the areas of management science, operation research and accountancy have examined the newsvendor problem; the newsvendor has to order a certain amount of newspapers to satisfy a stochastic demand. Note that in a wide variety of industries that deal with limited-useful-life products (i.e. flight- or hotel bookings, mobile phones), decision-makers face the same demand uncertainties as the newsboy. An often-referred study is Magee (1975), who presented one of the first extended Cost-Volume-Profit models to assess the newsboy problem by using capital asset pricing theory.

6.3 Towards a strategic portfolio

Let us consider an end-user who would like to meet her future electricity consumption V with a combination of forward contracts with different delivery periods. Let's assume for simplicity that she can choose between contracts that secure the delivery of load X in the first (M1), second (M2) and third (M3) upcoming month from the observation date. The long-range strategy that the end-user chooses is the following: 90% of the load V should be met in the first upcoming month of the observation day (day t), 70% of V in the second upcoming month from day t, and 40% in the third month from day t. She regards this purchasing strategy as her strategic benchmark, of which the sourcing mix can be managed over time (strategic portfolio management). Note that many other competing strategies exist. In textbox 6.1 we display the strategic benchmark (left-hand figure).



Textbox 6.1. Strategic benchmark to meet load V

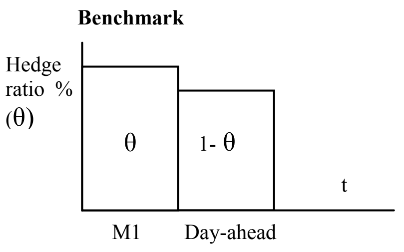
Let's consider an end-user who implements above-described purchasing strategy and can re-adjust her electricity derivative portfolio (in order to meet her consumption V) on every last trading day of each month in accordance with her benchmark (See figure 6.1). So on, let's say January 31, she follows her benchmark by entering into M1-, M2- and M3 contracts in such a way that respectively 90% of the demand load V is met by M1 contracts, 70% by M2 contracts and 40% by M3 contracts. She now has allocated her future consumption completely over these contracts. When she moves to the end of next

month, let's say February 27, she will purchase sourcing contracts in line with her strategic benchmark: In order to meet her strategic benchmark she has to purchase an additional 20% of the demand load in March through M1 contracts, in addition to the extent of V that has already been met in the previous month (70%) by the M2 purchase, in order to meet her consumption in March. This is depicted in the right-hand figure by the semi-transparent grey box.
In the same way, we can derive the amount that needs to be covered by what are now M2 contracts (previously M3 contracts), to cover the load obligation in April (not displayed). The percentages are the hedge ratios, as these tell us the extent to which the demand load V is met by M1, M2 and M3 contracts. Obviously the end-user can deviate from her strategic benchmark (e.g. she wants to exploit certain market opportunities), which is known in portfolio management literature as tactical asset management. The strategic portfolio structure consists of hedge ratios for the position different contract maturities. A point worth emphasizing is that today's day-ahead and forward markets provide end-users with the opportunities (i.e wide variety of market contracts) to implement a purchase strategy as discussed above. The key issue is to select the optimal purchase strategy (hence, the optimal hedge ratios) that matches the risk preferences of the end-user. We are interested whether the Markowitz theorem helps us to derive this strategy.

6.3.1 Model setting

Following the assumptions underlying the Markowitz framework, we assume that the participant is a mean-variance optimizer, who prefers fewer costs to more and can quantify her risk preference (see section 6.2, for a discussion on the key assumptions underlying this model). We apply the framework to a static one-period setting: Once the hedging position is decided, it is not changed after that during the whole investment horizon. Our model setting closely resembles the static one-period two-assets hedging framework examined in Vehviläinen and Keppo (2003). An important difference between the example described earlier and our model in this section, is that we consider a one-period model following Vehviläinen and Keppo (2003)[58]. This implies that we don't rebalance the position in the next month. We concentrate on the question whether portfolio theory can provide the end-user with the optimal hedge ratio (θ) that matches the risk preferences of the end-user.
As can be seen from textbox 6.2, the end-user in our model can allocate her consumption load V (expressed in MW) over two contracts: day-ahead contracts and M1 baseload contracts. $V(h,t)$ denotes the consumption on every hour h of day t in the first upcoming month from day $t = 0$. The end-user makes her purchase decision on day $t = 0$. The delivery period starts on hour $h = 1$ of day $t_1 = 1$ and ends on hour $h = 24$ of day $t_2 = 31$. An M1 baseload contract secures the delivery of 1 MWh at every baseload hour (all 24 hours of the day) in the first upcoming month from the observation date, against a fixed price F.

[58] We do not consider dynamic hedging strategies because of liquidity issues. A dynamic rebalancing setting would require that electricity spot and derivative markets offers sufficient opportunities of trade on every precise moment.



Textbox 6.2. Strategic benchmark to meet to meet load V(h,t)

We let the hedge ratio, θ, account for the extent that load V(t,h) is met by the M1 forward position. This position is noted as N, and expressed in units MW. We express θ as a percentage, where $0\% \leq \theta \leq 100\%$. When on any hour h of any day t in the delivery period V(h,t) has not been met by M1 contracts, the remainder is purchased (in case of deficit) or sold (in case of surplus) on spot, in the day-ahead market. Day-ahead spot contracts that secure the delivery of 1 MW power on a specific hour h of the next day against a price S(h,t). In this study it is assumed that the amount of electricity that needs to be purchased/ sold to meet V(h,t) is valued against the prices observed at the day-ahead market. This is a reasonable assumption, since the minimum time span given the technical constraints between trade and delivery is typically a one-day horizon (For more details, see Chapter 1 section 1). The day-ahead position is noted as Q(h,t), and expressed in units MW. In our model, we distinguish two load scenarios:
(i) constant load scenario; $V(h,t) = V_c$
(ii) time-varying load scenario V(h,t), with finite expectation $E_0(V(h,t))$ and variance $\sigma^2(V(h,t))$ over the delivery period. Here the expectation E_0 is taken at time t = 0, which denoted by the subscript.
It is important to emphasize that although the load profile V(h,t) can vary over time, the amount of electricity that is being delivered under the forward position is fixed, once the end-user sets θ. This is because we set N equal to the extent of the expected demand load $E_0(V(h,t))$ that the end-user wants to be met by the forward position N. Since the end-user selects sets the hedge ratio at t = 0, the forward price F and volume purchased at the forward market are determined at the exact same moment. We will denote this with the subscript 0, hence use the notation N_0 and F_0.
Another point worth noting is that the size of V(h,t) that has not been met by N, must be met by the spot position Q(h,t) that is also expressed in units MW. This means that any shortage or surplus amount of power is respectively purchased or such that V(h,t) is perfectly hedged on any precise moment. While the amount of power purchased on the forward market is fixed once the hedge ratio is set, this is not necessarily the case for the position Q(h,t). That depends on whether we assume a time-varying or constant load V(h,t).

We now can formulate the cost function of the purchase strategy. Let I(h,t) (θ) represent the cost function I(h,t) of the selected portfolio with hedge ratio (θ). It consists of a forward position component and day-ahead position component as can be seen here:

$$I(h,t)(\theta) = N_0F_0 + Q(h,t)S(h,t) \quad \text{where } 0\% \leq \theta \leq 100\% \tag{6.1}$$

6.3.2 Optimising electricity portfolio

We will now derive the mean-variance equations for both load scenarios.

(i) Constant load

When the demand load is constant, noted as V_c, the expected volume over the delivery period, noted as E_0 (V(h,t)), can be given by this single number, the constant V_c. The position on the forward market reads as:

$$N_0 = \theta\, E_0\, (V(h,t)) = \theta\, V_c \tag{6.2}$$

The remaining volume of that has not been purchased on the forward market, is purchased on the day-ahead spot market. Here represents Q(h,t) this position. We can write:

$$Q(h,t) = Q_c = (1- \theta)\, V_c \tag{6.3}$$

From equation (6.2) and equation (6.3) we can observe that once the hedge ratio θ is determined, both the size of the forward position N and the spot position Q(h,t), are known and constant over the delivery period. To illustrate that the spot position Q is constant on any time (h,t) in the delivery period, we replace the notation (h,t) by subscript c (see (6.3)). The portfolio cost function I(h,t)(θ) is:

$$I(h,t)(\theta) = N_0F_0 + Q_c\, S(h,t) = \theta V_c * (F_0-S(h,t)) + V_c\, S(h,t) \tag{6.4}$$

From equation (6.4) we can observe the term (F_0-S(h,t)) on the right hand side of the equation. This term looks similar to the forward basis examined in Chapter 5, but differs in as subtle way as in equation 6.4 the forward price is observed at t = 0, henceforth we do not consider the contemporaneous price differential between spot price and forward price. The expectation E_0 and the variance (var) of the portfolio costs I(h,t)(θ) are given by:

$$\begin{aligned} E_0\, [I(h,t)(\theta)] = \mu_\theta \quad &= \frac{1}{t_2 - t_1 + 1} \sum_{t=t_1}^{t_2} \sum_{h=1}^{24} [N_0F_0 + Q_cS(h,t)] \\ &= \frac{1}{t_2 - t_1 + 1} \sum_{t=t_1}^{t_2} \sum_{h=1}^{24} [V_c\, S(h,t) + \theta V_c * (F_0 - S(h,t))] \end{aligned} \tag{6.5}$$

We can see from equation 6.5 that when the electricity market participant decides to hold a long position in the forward (θ > 0), she pays a forward risk premium (herafter RP_0) for insulating herself for variation in electricity prices (price risk). When θ →1, the impact of the forward risk premium on the expected portfolio costs increases with the extent that the load obligation is covered by the forward position N_0, which is modeled by the constant volume θV_c.

$$\text{var}\,[E_0\,(I(h,t)(\theta))] = \sigma_\theta^2 = \frac{1}{t_2 - t_1 + 1}\sum_{t=t_1}^{t_2}\sum_{h=1}^{24} \text{var}\,[Q_c\, S(h,t)]$$
$$= \frac{1}{t_2 - t_1 + 1}\sum_{t=t_1}^{t_2}\sum_{h=1}^{24} \text{var}\,[Q_c\, S(h,t)] \qquad (6.6)$$

An important point worth emphasizing when examining equation (6.6) is that the constant Q_c can equal zero in one special case: when the hedge ratio is set equal to 100%. As can be seem from 6.6, the portfolios variance (σ_θ^2) will be zero as well. This implies that by fully hedging the price risk on the forward market, the price risk can be completely eliminated. In all other cases (when $\theta > 0\%$), the portfolios variance (σ^2_θ) equals the spot price variance multiplied by constant Q_c. From equation (6.5) and equation (6.6) we can recognize the trade-off that the investor faces: It involves the question whether the ex-post risk premium paid is worth offsetting the variation in portfolio costs, which stem from one source of risk only: the variation in price S(h,t). Any variation in portfolio costs arises from price risk. When we would assume load dynamics instead of a constant load profile, we will see that this will contribute to the variation in portfolio costs as well, besides price risk.

(ii) Load dynamics

Again we set N_0 equal to the extent of the expected demand load E_0 (V(h,t)) that the electricity market participants wants to cover by the forward position. Then N becomes:

$$N_0 = \theta\, E_0\,(V(h,t))\ , \text{ where } 0\% \leq \theta \leq 100\% \qquad (6.7)$$

We will use the average demand load as a proxy for E(V(h,t)).

Since the expectation E_0(V(h,t)) can be different from V(h,t) on any precise hour h of day t, the remainder of the size of the outstanding V(h,t) that has not been covered by N_0, is covered by the spot volume Q(h,t) that can vary on every precise moment. Q(h,t) reads as:

$$Q(h,t) = V(h,t) - N_0 = V(h,t) - \theta\, E_0\,(V(h,t)) \qquad (6.8)$$

From equation (6.8) we can observe how the oscillation of V(h,t) around it's expected level E_0(V(h,t), affects the spot volume Q(h,t) on any precise moment. It can be seen that the hedge ratio θ scales the size of the spot volume Q(h,t), but does not affect the variation that is embedded in the demand load V(h,t) since it is a constant over the investment horizon.

The variation in V(h,t) is likely to be higher on certain hours h (peak hours) and /or certain days t (weekdays), when demand load uncertainty is higher. On off-peak times (night hours, weekends and holidays) the spread around the expected load will be lower, as will demand load uncertainty. Hence, these fluctuations embedded in the deterministic demand load V(h,t) are effectively hedged on the day-ahead spot market with an hourly-varying volume Q(h,t).

In the following equation we read the cost function of the portfolio costs I(h,t)(θ):

$$I(h,t)(\theta) = N_0F_0 + Q(h,t) * S(h,t) \qquad (6.9)$$

We can see from equation (6.9) that the second term on the right-hand side of the equation is accounts for load dynamics that have been introduced: Hence, a time-varying volume of size Q(h,t) needs to be purchased against day-ahead price S(h,t).

When we examine (6.9), two points are worth emphasizing: When V(t,h) is time-varying and oscillates around the expected level E_0 (V(h,t)), there exists no hedge ratio (i.e. θ = 100%) that the electricity market participants can select to fully eliminate the portfolio risk. We do not impose sale constraints, which implies that when the volume of the forward position N_0 exceeds the actual demand load this volume surplus can be sold against S(h,t)

We now derive the expected purchase costs E [I(h,t)(θ)]:

$$E_0 [I(h,t)(\theta)] = \mu_\theta = \frac{1}{t_2 - t_1 + 1} \sum_{t=t_1}^{t_2} \sum_{h=1}^{24} [N_0 F_0 + Q(h,t)S(h,t)]$$
$$= \frac{1}{t_2 - t_1 + 1} \sum_{t=t_1}^{t_2} \sum_{h=1}^{24} [V(h,t)S(h,t) + \theta E_0 (V(h,t)) * (F_0 - S(h,t))] \tag{6.10}$$

To see how the price and loead profile affects the variance (var) of I(h,t)(θ), we examine:

$$\text{var} [E_0 (I(h,t)(\theta))] = \sigma^2_\theta = \frac{1}{t_2 - t_1 + 1} \sum_{t=t_1}^{t_2} \sum_{h=1}^{24} \text{var} [Q(h,t) S(h,t)]$$
$$= \frac{1}{t_2 - t_1 + 1} \sum_{t=t_1}^{t_2} \sum_{h=1}^{24} \text{var} [Q(h,t) S(h,t] \tag{6.11}$$

We can see from equation (6.11) that the portfolio variance estimate σ^2_θ, equals the variance in day-ahead market costs Q(h,t)S(h,t). An important difference between the mean-variance expressions of this scenario and scenario (i), is that now there does not exists a hedge ratio θ by which the portfolio cost risk (proxied by σ^2_θ) can be completely eliminated. This is because Q(h,t) is a time-varying variable, hence contributes to portfolios variance.

Measuring electricity cost risk

In order to use a VaR-like measure as a risk constraint to select the optimal portfolio along, I(h,t)(θ) should have a finite expectation and variance. We have seen that this applies for the portfolio cost function in both load scenarios (i) and (ii). An important condition to write the portfolio risk in terms of VaR is that the tail area of the I(h,t)(θ) distribution can be assessed accurately. This can be done for a variety of distributions: i.e. Student-t distribution, normal distribution or lognormal distribution.

In this study we examine the costs of electricity purchase strategies from an end-user perspective. Several studies have been published that examine the portfolio distribution from the perspective from the counterparty, hence these studies concentrate on the distribution of electricity sales strategies. The special edition Vol. 9 (1) of the Journal of Econometrics (1979) gives an excellent overview of this stream in the energy economics literature. We are not aware of any empirical studies that examine the electricity 'costs' or electricity 'sales' in the post-privatisation era. Also studies on modeling electricity loads are very scarce. Nowicka-Zagrajek and Weron (2001) concentrate on electricity hourly load dynamics in the Californian power market in the period 1998 to 2001, and find that the distribution of deseasonalized hourly power loads exhibit excess kurtosis. A point worth noting is that part of the data sample overlaps the Californian power crisis in 1999

and 2000, which could influence their results. Studies on electricity price modeling dominate this field of academic research; Pilipovic (1998), Lucia and Schwartz (2002), Bessembinder and Lemmon (2002) have documented empirical evidence obtained from major power markets around the world, that electricity day-ahead prices have a positively skewed distribution, which typically exhibit high excess kurtosis. The assumption that the price distribution around the expected electricity spot price value follows a lognormal distribution, is being imposed to the power portfolio selection problem studied in Vehviläinen and Keppo (2003).
The lognormal distribution is a monotonic transformed version of the normal distribution. This means that a random variable X is lognormal when its natural logarithm, noted as ln (X), is normal. The lognormal distribution can be described by a parameter to measure its arithmetic mean μ and a parameter σ for estimating the spread around the mean. The minimum value of a lognormal distribution is zero, and it has a positively skewed bell shape form. We argue that these characteristics are arguments in favor for assuming that the cost distribution $I(h,t)(\theta)$ follows a log-normal process. First, as we only need ensure that the expectation and variation of the costs function are finite we can solve our portfolio problem in a two-dimensional mean-variance space. Second, the fact that the minimum value of the lognormal distribution is zero, resembles the distribution features of the cost function $I(h,t)(\theta)$ since costs can never be smaller than zero. We will empirically test whether this assumption holds.

We transform $I(h,t)(\theta)$ to its lognormal value, noted as $\bar{I}(h,t)\,(\theta)$ value, such that:

$$\bar{I}(h,t)\,(\theta) = \ln\left(I(h,t)\,(\theta)\right), \text{ where } \bar{I}(h,t) \sim \mathrm{IID}\,(\mu, \sigma) \tag{6.12}$$

Here ln stands for natural logarithm. Then we can write for the cumulative distributional function F (cdf) of $\bar{I}\,(h,t)\,(\theta)$:

$$F\,(\bar{I}\,(h,t)\,(\theta)) = P\,(\bar{I}\,(h,t)\,(\theta) \leq \pi_{h,t}) = c \quad \Rightarrow \quad \pi_{h,t} = F^{-1}\,(c) = q\,(c) \tag{6.13}$$

Here P stands for the probability of occurrence and q refers to the quantile at c of the cdf. Then P is given by the c^{th} quantile of cdf $\bar{I}\,(h,t)\,(\theta)$ namely such that:

$$P\,(\bar{I}\,(h,t)\,(\theta) \geq \mathrm{VaR}) = c \tag{6.14}$$

Here P stands for the probability of occurrence and q refers to the quantile at c of the cdf. A VaR p/day value of €x implies that the market participant can be (100-c)% certain that the costs in excess of the daily average costs are equal to €x. Then P is given by the c^{th} quantile of cdf $\bar{I}\,(h,t)\,(\theta)$ namely such that:

$$\mu_\theta = \mathrm{VaR} + q(c)\sigma_\theta \tag{6.15}$$

We observe from equation (6.15) that when we assume that the cdf of $I(h,t)\,(\theta)$ can be approximated by a lognormal distribution, the quantile estimate is merely a multiple of standard deviations. In this framework we can easily express the investor's choice for the optimal hedge ratio that results in the portfolio that minimizes (Min_θ) the expected portfolio costs subject to VaR as described in equation (6.13). For the function $\bar{I}\,(h,t)(\theta)$ it should hold that:

$$\mathrm{Min}_\theta \left\{E\,[\bar{I}\,(h,t)\,(\theta) \mid P\,(I(h,t)\,(\theta)) \geq \mathrm{VaR} = c \right\} = \mathrm{Min}_\theta\, \mathrm{VaR} + q(c)\,\sigma_\theta \tag{6.16}$$

We note that the equation only holds when q(c) is smaller than zero, which is the case when the confidence level c is very small. In this study we set c equal to 1% or 5%, hence we set our risk limits respectively at the 95%VaR and 99% VaR. Furthermore note that $\bar{I}(h,t)(\theta)$ can be easily transformed to the actual value $I(h,t)(\theta)$, by taking the exponential of $\bar{I}(h,t)(\theta)$.

6.4 Data and sample description

We use hourly price and load data from the Dutch wholesale power market for the month January 2004, being 744 observations each. From Tennet we obtain the load profile scheme for this month. In this scheme, the load fractions forecasts for the month January 2004 are specified on a 15 minutes basis, being 2976 observations in total. The fractions add up to 1.

Tennet distributes these schemes to all the Program Responsible (PR) firms[59]. PR firms are using the load profile schemes as a measure for the electricity demand of small parties with an installed capacity that is equal or smaller than 100 KW. A small commercial building typically uses 100 KW (Bunn, 2004). For parties connected to the grid, which have an installed capacity higher than 0.1 MW, the PR firms generally rely on installed systems measure the electricity consumption/supply on a 15 minutes basis. However, installment and maintenance of this measurement equipment is not always economically feasible, so even for this group of customers it is not uncommon to use the load profile schemes as a measurement tool for their consumption. We use the load fractions to derive a time-varying load function V(h,t) that we use in this study. We assume that the electricity market participant has a contractual obligation to deliver 100 MW per hour, which we refer to as the index. When we multiply the hourly fraction with the index, we get the time-varying load function V(h,t). Therefore the expectation of the demand load E(V(h,t)), proxied by the average demand load, and the constant demand load V_c, both equal the index.

In figure 6.1 you can see the constructed load dynamic function V(h,t) for the month January. From the figure, we observe that the demand load in the night and morning hours are low and typically varies between 50 MWh and 100 MWh. In the hours 18 to 22, often referred to as the super peak hours, electricity consumptions is highest and around 140 MWh to 160 MWh.

[59] We refer to Chapter 2 section 3.1, for a discussion on PR firms in the Dutch power market system.

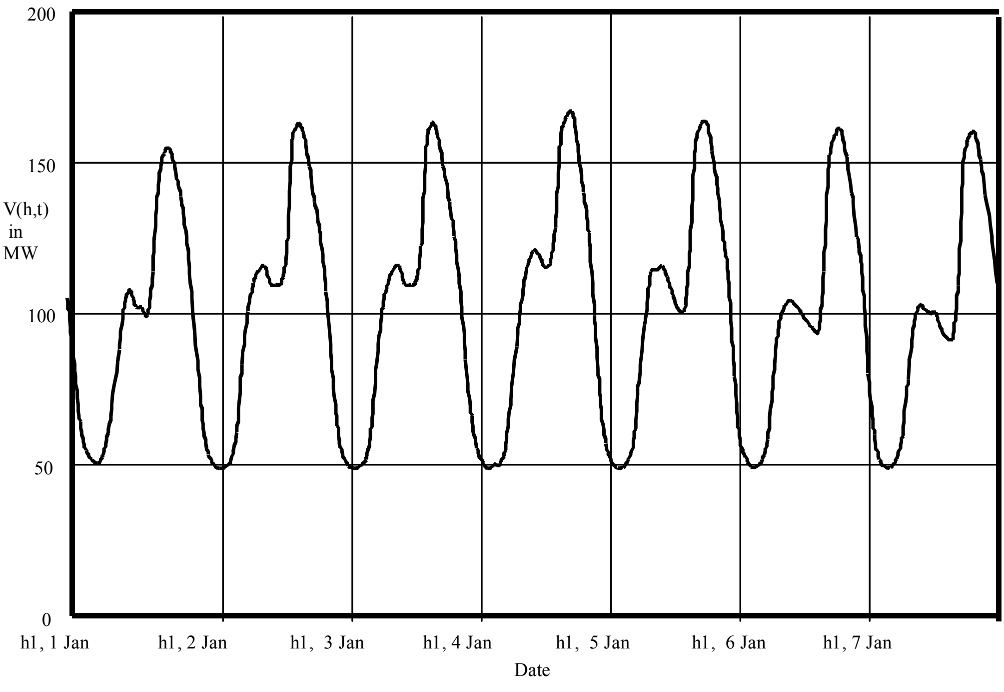


Figure 6.1: Load dynamics V(h,t) in MW for Dutch market (1 to 7 January 2004).

From the Amsterdam Power Exchange we obtain hourly day-ahead baseload prices for the month January 2004. In table 6.1, we provide the descriptive statistics of the hourly volumes V(h,t) and hourly prices S(h,t) in January 2004. From table 6.1, we observe that the average hourly base load is 100 MWh. Note that we have multiplied the hourly fractions obtained from the load schemes, which add up to 1 over all 744 hours in the delivery period, with this amount. In particular, we have assumed that the hourly load obligation is equal to 100 MWh. Therefore it directly follows that the average base demand load is (74400 MW/ 744 hours=) 100 Mwh.

Note that we set the expected monthly load E(V(t,h)) equal to this estimate in the scenarios under consideration. From the standard deviation estimates listed in table 6.1, we can see that the dispersion of the load V(h,t) around it's expected value of 100 MW is higher than the dispersion of the price S(h,t) around it's expected value of €30.86 p/MWh. When we would consider the standard deviation estimates as meaningful measures for the variation in price and load profile, we conclude that the contribution of the 'volume risk' to the total portfolio risk is highest. From the skewness estimates that are close to zero, and negative excess kurtosis estimates we conclude that the distribution of V(h,t) has no fatter tails than the normal distribution.

	Load V(h,t) (MW)	Price S(h,t) (€/MWh)
Mean	100.0	30.86
Median	101.9	28.09
Std deviation	34.93	21.67
Minimum	49.22	0.050
Maximum	168.1	396.1
Skewness	0.112	8.177
Exc. Kurtosis	-0.994	117.5

Table 6.1: Descriptive statistics of demand load and spot prices on Dutch market for January 2004

The high positive skewness and excess kurtosis of the price S(h,t), disclose the non-normal characteristics of hourly price data discussed in Chapter 3. The comovement between the price S(h,t) and load V(h,t), as measured by the correlation coefficient equals 0.12 in January 2004 (and 0.11 in year 2004).[60]

As mentioned earlier, the end-user makes her portfolio selection choice on day t = 0, before the delivery period starts (on hour 1 of January 1, 2004). We set t = 0 equal to 30 December 2003, which is the last trading day of this month that forwards are traded. On this day, the M1 baseload forward price is €48.72. This price is close to the average M1 forward price in that month, being €47.86. This forward contract secures the delivery of 1 MWh on each hour of the day. The daily base forward premium RP_0 equals €428.6 (€17.86*24h) for delivery of 24MWh, which is calculated as the difference between the forward price and the monthly averaged hourly day-ahead price that equals €30.86 (See table 6.1).

6.5 Results

In section 6.5.1 we construct the efficient frontiers for scenario (i) and (ii) from solving our extended Markowitz equation framework that we have developed in section 6.3. We refer to Appendix A6.1 for the cost-risk measure statistics. We elaborate on the implications that can be drawn from these results. In section 6.5.2 we show and discuss the results of the optimal portfolio choice when the end-user sets her VaR-like preference.

60 A similar degree of comovement is observable between the day-ahead prices and day-ahead trading volumes observed in the APX market in that period. That is, a negative correlation coefficient of 0.17 in January (and -0.07 in year 2004).

6.5.1 Delineating efficient frontiers

In figure 6.2 we display the efficient frontiers corresponding to the two load scenarios (i) and (ii), which are delineated in an expected cost - risk space. Here we have chosen the confidence level for our VaR limit at 95%. Any cost-risk measure (Total I(h,t)(θ), μ_θ p/day, σ_θ p/day, VaR p/day) mentioned in this section, can be found in the tables A6.1 and A6.2 of the Appendix.

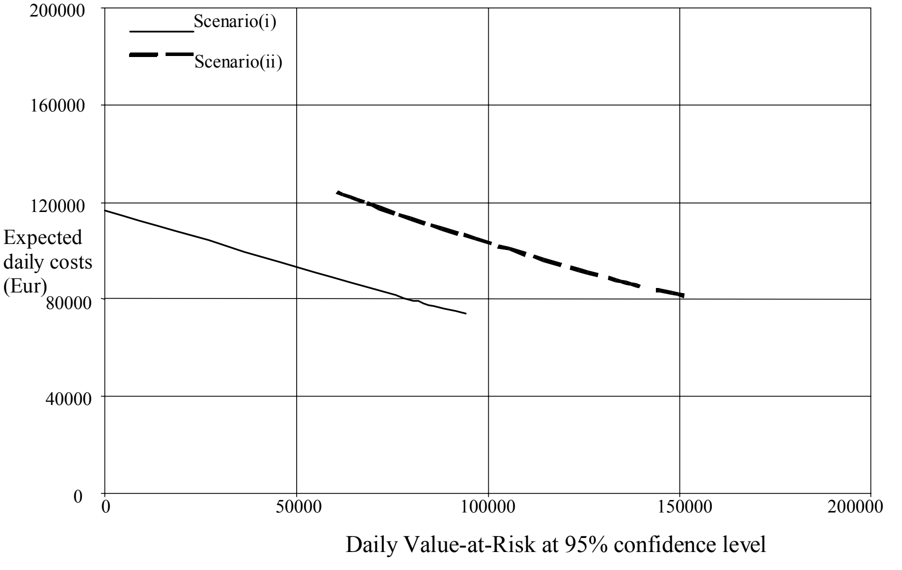


Figure 6.2: Efficient frontiers scenarios (i) and (ii) - 95%VaR -

Each of the two efficient frontiers displayed in figure 6.4, extends from the minimum risk portfolio (most left point on frontier) to the minimum cost portfolio (most right point on frontier). These are respectively the ENDEX portfolio (θ = 100%) and APX portfolio (θ = 0%). The ENDEX portfolio is the most expensive portfolio and the APX portfolio the cheapest along the efficient frontier.

From the negative slope of both efficient frontiers, we can conclude that a higher risk appetite is rewarded with lower expected costs.[61] This result is important. The downward trend of expected portfolio costs with risk is consistent with the Markowitz portfolio theory. We can see from the efficient frontier corresponding with scenario (i) that the ENDEX portfolio is risk-free. This portfolio with hedge ratio θ = 100% has a daily VaR that equals €0 p/day, hence the portfolio cost risk can be completely eliminated. A VaR p/day value of €0.00 implies that the end-user who selects the portfolio (θ = 100%) can be

[61] The choice for a higher confidence level for the VaR limit (e.g. 99%VaR) does not affect this conclusion. The increase of the confidence level of VaR implies that the portfolio VaR increases.

certain that the costs in excess of the daily average costs of €116928 are equal to €0.00. These figures can be found in table A6.2 of the Appendix.
From equation (6.6) we have seen that the source of portfolio risk in scenario (i) is price variation on the spot market. We can see from the efficient frontier corresponding with scenario (ii) that there exists *no* such efficient portfolio (θ) when the demand load V(h,t) is time-varying. This is because the introduction of load dynamics into the model, implies that an additional source (besides portfolio price risk that stems from S(h,t)) of risk is introduced in the mean-variance framework. This risk essentially stems from the load profile V(h,t) (see equation 6.11). In contrast with scenario (i), risk cannot be completely eliminated (only reduced) through investing in the ENDEX portfolio in scenario (ii). The daily average costs of this purchase strategy equal €124212 and the daily 95%VaR (99%VaR) equals €60422 (€61394) p/day. Hence, the end-user can be 95% (99%) certain that the costs in excess of the daily average costs are equal to €60422 (€61394) per day. The horizontal move[62] of the efficient frontier to a higher risk space that we observe when we move from scenario (i) to (ii), thus stems from the fact that in scenario (i) the day-ahead spot position Q_c is constant over time, while in scenario (ii) this position is time-varying Q(h,t). Observe that there exists no efficient portfolio (θ) in both scenarios with the exact same cost-risk profile. Also observe that the slope of the efficient frontiers is the same and amounts a daily average costs (μ_θ p/day) of €428.6 per percent increase in θ. This is equal to the daily risk premium that the holder of an M1 contract pays per contract, namely: $RP_t(T)$*24h = €17.86*24. The end-user's motivation to pay the forward premium is to insulate herself from portfolio cost risk. This explains the increase in portfolio costs that we observe in figure 6.4, when we move along the frontier such that $\theta \rightarrow 100\%$.

An important point that has not been examined yet is whether the lognormality assumption imposed on our empirical distribution I(h,t)(θ) holds. We therefore plot the quantiles of the $\bar{I}$ (h,t) (θ) distribution (the lognormal transformation of I(h,t)(θ)) against the quantiles of a normal distribution (Q-Q plot). In Appendix A6.4 and A6.5, we provide the Q-Q diagrams that corresponds with the cost distributions of the portfolios that lie on the efficient frontiers that are displayed in figure 6.2. These diagrams suggest that the VaR measure is subject to possible under- or overestimation of the true risk faced.

6.5.2 Results optimal portfolio selection

The final step in the sourcing allocation process is to choose the portfolio from the efficient frontier displayed in figure 6.4, which meets the VaR-like preference of the market participant. For the sake of illustration, let's assume that the end-user can quantify her portfolio risk appetite in VaR terms and sets her daily (100-c)% VaR limit equal to €75000 p/day. Here c equals 1 or 5%. This implies that she wants to be 95% or 99% certain that the

[62] This move is not completely horizontal. The level of portfolio costs (μ_θ p/day) is slightly higher in scenario (ii) than in (i), as can be seen from the Appendix (compare results A6.1 and A6.2). This can be explained by the fact that that in scenario (ii) the spot-volume Q(h,t) can be different on every precise moment. In scenario (i) the spot-volume is constant (Q_c). Especially on moments when a relatively large amount of power needs to be purchased on the spot market against a relatively high price S(h,t), these costs have a relatively higher contribution on total portfolio costs. We note that the low value of correlation between S(h,t) and V(h,t), being 0.12, the chance of occurrence is rather low.

costs in excess of the daily average costs are equal to €75000. This VaR level is chosen randomly.[63]

	Scenario (i)		Scenario (ii)	
	95% VaR	99% VaR	95% VaR	99% VaR
Optimal (θ)	18%	20%	81%	83%
μ_θ p/day	€81948	€82846	€115951	€116725
σ_θ p/day	8664	8442	8454	8293

Table 6.2: Optimal portfolio under Value-at Risk like measure (Equation (6.16))

From table 6.2 we can see that when the end-user has a constant consumption pattern and wants to be 95% or 99% certain that her costs in excess of the daily average costs will not exceeds €75000 per day, she selects a portfolio with hedge ratio of respectively 18% or 20%. When the end-user has a time-varying consumption profile, she selects a portfolio with a hedge ratio of 81% (95% VaR) or 83% (99% VaR). The choice for a higher confidence level translates to a higher proportion of the demand load V(h,t) that needs to met by the riskless forward position, in order to satisfy the same VaR limit set by the end-user (€75000 p/day).

6.6 Concluding remarks

Today's spot and derivative markets provide end-users with the opportunities to implement a purchase strategy that is consistent with their risk appetite. In this Chapter we provide empirical evidence obtained from a basic portfolio model that the theory of efficient portfolios proposed by Markowitz (1952), and additions that incorporate a Value-at-Risk based risk measure, can help her to do that. We provide an empirical analysis using two different market contracts and assume a deterministic load profile. Our results demonstrate that mean-variance portfolio theory structures the sourcing, in such a way that is consistent with her risk appetite. This result is important. We claim that our proposed method provides a framework for mapping the risk appetite to market contracts. Firms that use electricity in a certain profile can select a purchase strategy that is consistent with their risk aversion level. The proposed method for electricity portfolio selection structures the sourcing. As such, the framework can be regarded as an important step towards the formulation of a strategic portfolio that can function as an independent benchmark that traders may use to evaluate their tactical deviations (e.g. trader might decide to exploit her timing skills) along.

[63] The objective of this study namely is to show that mean-variance portfolio theory can be applied to find optimal hedge ratios in electricity markets.

6.7 Appendix

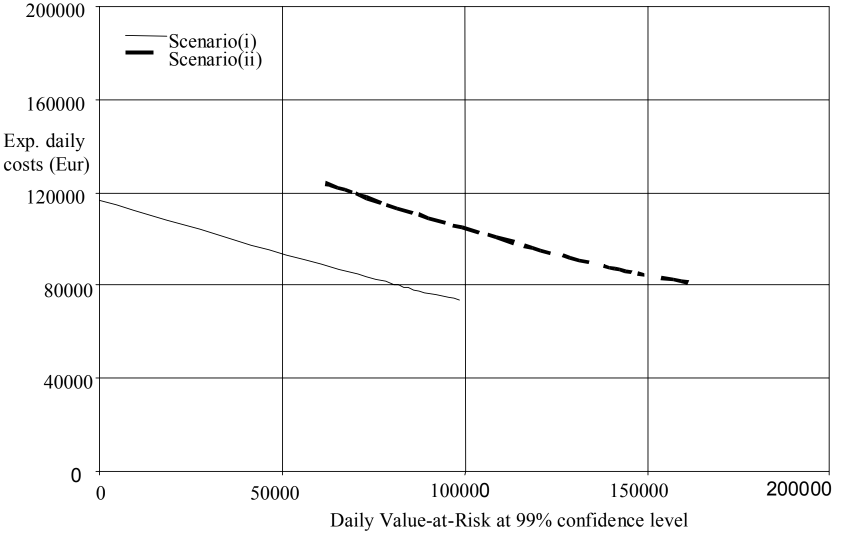


Figure A6.1: Efficient frontiers scenarios (i) and (ii) - 99%VaR -

Portfolios on efficient frontier scenario (i) in Figure 6.2
Selection is based on a step-size of 10% for θ.

	Equation	θ = 0%	θ = 10%	θ = 20%	θ = 30%	θ = 40%	θ = 50%
μ_θ p/day	(6.5)	74064	78350	82637	86923	91209	95496
σ_θ p/day	(6.6)	10617	9555	8494	7432	6370	5309
95%VaR p/day	(6.20)	94208	83121	73473	64070	54784	45565
99%VaR p/day	(6.15)	98557	85915	75496	65529	55813	46261
		θ = 60%	θ = 70%	θ = 80%	θ = 90%	θ = 100%	
μ_θ p/day	(6.5)	99782	104069	108355	112642	116928	
σ_θ p/day	(6.6)	4247	3185	2123	1062	0	
95%VaR p/day	(6.15)	36390	27247	18131	9045	0	
99%VaR p/day	(6.15)	36829	27494	18243	9074	0	

Table A6.2: Cost risk measures for efficient portfolios in scenario (i)

Portfolios on efficient frontier scenario (ii) in Figure 6.2
Selection is based on a step-size of 10% for θ.

	Equation	θ = 0%	θ = 10%	θ = 20%	θ = 30%	θ = 40%	θ = 50%
μ_θ p/day	(6.10)	81355	85641	89926	94212	98498	102783
σ_θ p/day	(6.11)	16356	15339	14327	13324	12330	11348
95%VaR p/day	(6.15)	151400	138733	128625	119090	109890	100945
99%VaR p/day	(6.15)	161154	145607	134047	123455	113432	103824
		θ = 60%	θ = 70%	θ = 80%	θ = 90%	θ = 100%	
μ_θ p/day	(6.10)	107069	111355	115640	119926	124212	
σ_θ p/day	(6.11)	10383	9437	8520	7639	6811	
95%VaR p/day	(6.15)	92232	83763	75581	67760	60422	
99%VaR p/day	(6.15)	94569	85652	77101	68977	61394	

Table A6.3: Cost risk measures for efficient portfolios in scenario (ii)

Q-Q plot
The shape of this Q-Q plot should be a straight line if the theoretical distribution correctly describes the empirical distribution $\bar{I}$ (h,t) (θ). If they don't, there is a mismatch: a concave (convex) shape indicates that the empirical distribution is positively (negatively) skewed. If the diagram has a straight line in the middle and curves upward (downward) at the left end downward (upward) at the right, it would indicate that the empirical distribution has thicker (thinner) tails than the normal distribution.

A6.4 Q-Q plot scenario (i)

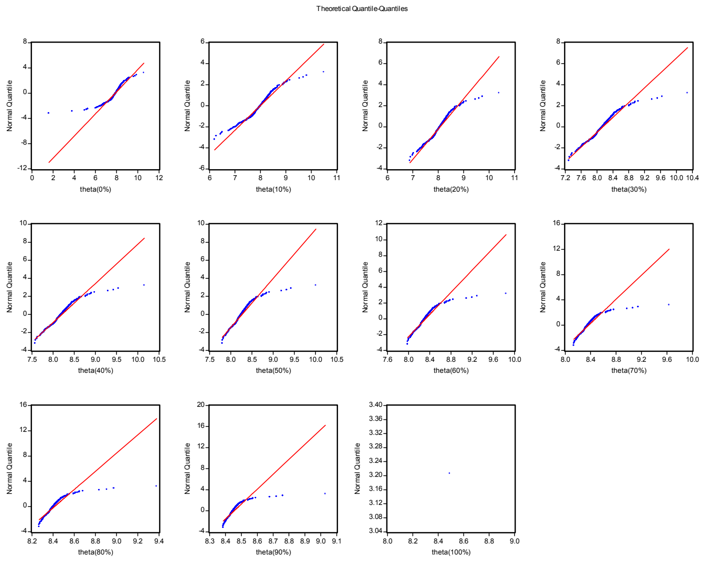


Figure A6.4. Quantiles of $\bar{I}$ (h,t) (θ) distribution against quantiles normal distribution for scenario (i). Corresponding with portfolios (θ) in table A6.2

A6.5 Q-Q plot scenario (ii)

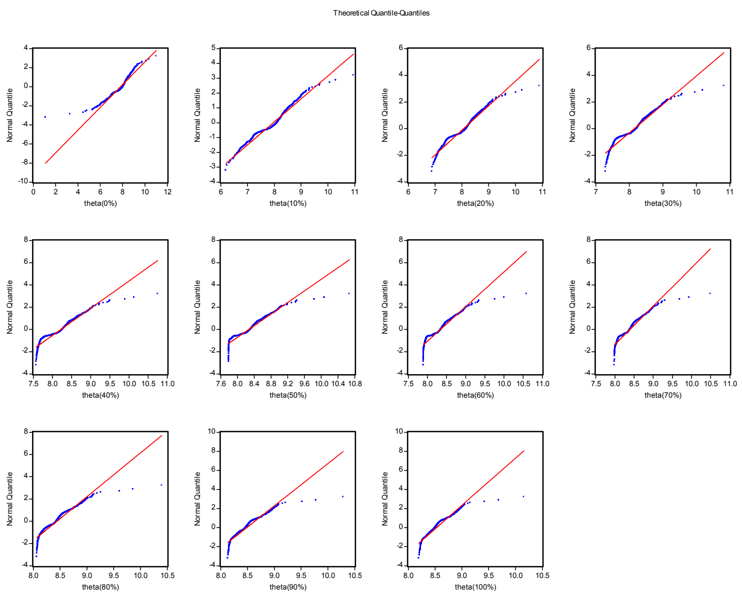


Figure A6.5. Quantiles of $\bar{I}$ (h,t) (θ) distribution against quantiles normal distribution for scenario (ii). Corresponding with portfolios (θ) in table A6.3

Chapter 7: Conclusions

7.1 Concluding remarks

The single main conclusion that can be drawn from the research issues outlined in the previous chapters, is that the introduction of competitive wholesale power markets has resulted in price modeling and portfolio management puzzles that share both features observed in traditional markets, and distinct features that are unique for this market. Therefore the empirical studies discussed in this thesis, suggest additions to the traditional models of the financial markets, to make them applicable for electricity markets. The main conclusions and implications that can be drawn from the findings presented in this Thesis, will be discussed in this Chapter.

7.1.1 Electricity spot price modeling

Since the worldwide deregulation of the power industry that started in the early 1990's, market places have been created on which market participants can trade electricity for different delivery periods in future or in real-time. In Chapter 2 we concentrate on two of these market platforms, the day-ahead market and balancing market. These markets play an essential role in ensuring the real-time balance between supply and demand at every precise moment in time. We examine whether the historical development of price and volumes obtained from these markets are consistent with the increase of efficiency imposed by the liberalization. A central objective of the EU policy is to establish a free internal energy market through liberalization by increasing efficiency. We shed light on this issue by examing part of the market. We obtain data from the Dutch power market, and find that both imbalance prices and the spread between this price and the day-ahead price increase, and that unbalance volumes decline. The price increase can be explained by allocative efficiency as cheaper production facilities are better allocated in the merit order of the day-ahead market and that only more expensive production facilities are available for unbalance volume. The volume decrease can be explained by improved demand forecasts of energy firms, which leads to fewer shocks to the system. This has a positive effect on the security of supply as long as a minimum reserve level is maintained. The provided evidence indicates that the energy resources are better allocated in terms of production costs and that energy firms have improved their forecasts on consumer demand. Although our study covers only part of the market, the results are promising in light of the EU objective to increase efficiency in the electricity system.

In Chapter 3 and 4 we examine the price dynamics of day-ahead contracts that secure the delivery of electricity on the next day. Understanding these dynamics is essential to explain the risks and rewards to which participants in today's deregulated industry are exposed. In Chapter 3 we focus on the dynamics of the daily average of these prices. The dynamics of daily prices are important as these prices are used as reference point for marking to market valuations and serve as a base for option contracts such as callable options. In this Chapter, we concentrate on the extreme events. Here 'extreme' refers to the chance of occurrence that an extreme price movement occurs and is captured by the tails of a return distribution, in our study the distribution of the residuals of a mean-reverting price model. The fatter the tail, the more tail probability mass, henceforth the higher the risk that market participants will face. We use the tail fatness estimator proposed by Huisman et. al (2001) that is one of the very few estimators that has proven to be unbiased in small samples. It therefore ensures us to assess the amount of tail fatness correctly in small samples, which are typical for electricity prices (due to the short market existence). We then use this information to parameterize a Student-t distribution. We propose the Student-t distribution as an alternative to the normal distribution as it is capable of capturing the fat tailed behaviour of electricity prices. We demonstrate that assuming normal innovations in Monte Carlo simulations for risk management purposes can have serious consequences for the true amount of risk faced. We consider our method an easy-to-implement alternative to other power price models proposed in literature, such as jump diffusion models or switching regimes models that also explicitly model extreme events and allow for incorporating additional risk that stems from non-normal characteristics. Our proposed method enables risk managers and portfolio managers to assess the true price risk that they face in today's volatile electricity markets. The average prices examined in Chapter 3 are indeed averages and do not meet the market microstructure of the day-ahead market itself. Chapter 4 therefore provides a satisfactory empirical framework to describe the dynamics on an hourly (intra-day) basis, and more importantly, exactly matches the market microstructure of day-ahead markets. Prior research has failed to do that. The results, obtained from our proposed panel framework, show clearly that hourly electricity prices vary throughout the day: In the midnight-, morning-, and evening hours during weekdays, and all hours in the weekend, prices are below the daily average mean. Prices are higher than the daily average prices for on-peak delivery of power (power delivery in business hours). These estimates make sense as demand for power is low in weekend and off-peak hours on weekdays, and high in peak hours. This finding implies that a price model with a daily average mean will not suffice, hence will lead to erroneous conclusions. Other important findings on hourly stochastic patterns show up in the cross-sectional correlation matrix of the error term of our hourly price model: We find a strong correlation between prices of two adjacent hours. An explanation for this effect is that when reserve capacity is low in one hour it will probably be low in the next hour as well and if demand is high in one hour it will probably be high in the next hour as well. A second major finding is the intra-dayblock correlation structure between hours. The first block is identified in the morning-, and midnight hours. Prices in these off-peak hours exhibit high cross-sectional correlations. The second block shows up in the peak hours from hour 6 through hour 19. Again prices in these hours are highly correlated. There is evidence for a clear peak versus off-peak correlation structure but, interestingly, the boundaries of the peak block do not perfectly match the market definition of peak hours. These findings have important implications for market participants on both the supply and demand side: e.g. Power generation plants let their nomination depend on the expected prices for electricity delivery throughout the day. Firms that use electricity in a certain profile through the day that can't be resembled by standard base- or peakload contracts might have a demand for contracts that deliver only in a few hours of the day. To valuate these contracts market makers need to assess the expectations and risks for those specific hours and cannot rely on daily average prices only. Applications of our proposed panel framework can be found in power risk management and derivative pricing.

7.1.2 Electricity derivative price modeling

In Chapter 5, we follow a modeling approach that allows us to jointly measure the fractions of risk premia and forecast power to day-ahead prices changes embedded in forward-, or future prices. We do this for a range of different month-ahead contract maturity horizons. We find that the premium component follows a downward trend with maturity, while the forecast component follows an opposite time-to-maturity pattern. This can be explained by

the mean-reverting behavior of the underlying spot price process: for forward-, or future contracts with long maturities, its price is not likely to react on the underlying spot price, since the day-ahead price expectation will be around the long-term mean. Therefore the forward-, or future price is an almost unbiased predictor of the day-ahead price, hence the forecast component (risk premium) component is large (small). However, when we roll to the expiration date as close to one-month before expiration, the chance of occurrence that the spot price will be close to the long-term mean decreases. The holder of a forward- or future contract requires a higher compensation for the increased uncertainty, which translates in a higher risk premium component (and lower forecast component) embedded in the forward-, or future price of short maturity contracts. This evidence is consistent with the well-known Samuelson effect observed in many commodity derivative prices that tells us that when there is a mean-reverting spot price process, the return volatility of a derivatives contract monotonically rises when the contract approaches its expiration date.
Another main finding is that forward-, and future prices convergence (to a certain degree) to spot price expectations when the expiration day is approached. This is an important result because the threat of arbitrage that keeps the forward-, or future price in line with the underlying spot price is absent in electricity markets (due to the non-storability of electricity). Further research should provide conclusive results whether market makers valuate electricity contracts as if the no-arbitrage condition still applies. Our findings have important implications for agents who need to assess risk premia and price expectations: E.g. agents that have a certain future demand load, may want to prefer to hedge against price risk by taking positions in contracts with long maturities (opposed to short maturity contracts), since these contracts embed a relatively low premium component. The documented results give traders and risk managers insight in the risk premia and might help to assess price expectations. One typical application of our result is setting mean price levels in simulation models that produce potential price patterns for future time periods. A fraction of the forward price can be used as a good predictor for future prices as it reflects the market expectation on the change in day-ahead prices. Here the size of this fraction is a function of the time to maturity of the contract.

7.1.3 Electricity portfolio management

As a result of the worldwide liberalization in electricity markets, risk has been transferred through the industry chain from the supply side to the end-user. While she used to rely on one regulated power price that seldom changed, she now has to deal with the economic law of demand. This requires that she has to act in order to exploit the lowest price, find the best service offered by suppliers, or select the best purchase strategy for electricity delivery on spot or in a future delivery period ahead. Hence, in today's markets she needs to assess her risks and expectations, and in Chapter 6 we concentrate on a conceptual framework that can help her to do that. We address the question of an end-user who wants to define an optimal purchasing strategy to allocate her future electricity demand load over a combination of day-ahead contracts and forward contracts, in such a way that this strategy matches her risk preference. Prior research has failed to provide a satisfactory empirical framework that considers hedging the electricity load dynamics with static forward strategies. We test whether a Markowitzian based optimization framework can be applied to derive the optimal hedge ratio for the position different contract maturities. Here the mean is considered as a meaningful measure for the expected portfolio costs, and the portfolio risk is quantified by a Value-at-Risk (VaR) like measure that allows for

incorporation of additional risk that results from any non-normal behavior in the power portfolio cost distribution. The degree of risk aversion is set according to the VaR limit chosen by the agent. The portfolio is then selected by minimizing the expected portfolio costs subject to the level of risk, hence yields the efficient portfolio. We use this framework to delineate the efficient frontiers for a basic load profile, which extend from the minimum risk portfolio (most left point on frontier) to the minimum cost portfolio (most right point on frontier). From this we can conclude that a higher risk appetite is rewarded with lower expected costs. Our main finding is that our Markowitzian portfolio selection approach structures the sourcing, henceforth matters.
These findings have important implications for agents who want to select a power portfolio strategy that is consistent with their risk appetite: the proposed method provides a framework for mapping the individual risk appetite of the agent to market contracts. Companies that use electricity in a certain profile can select a purchase strategy that is consistent with their risk aversion level. The proposed method for electricity portfolio selection structures the sourcing. As such, our approach can be regarded as an important step towards the formulation of a performance measure that can function as a strategic benchmark for portfolio investors who want to manage the sourcing mix over time. The activity of tracking the index, known as indexation, is widely used by investors in the traditional financial asset (e.g. bond or stocks) area.

7.2 Further research

The deregulation that has been imposed by many governments on the electricity industry of their country has been a complex task, due to the unique characteristics of electricity and its price behavior. For instance, the fact that in many countries only a few players dominate the market, influences the extent to which the market rules of demand and supply are implemented fairly. A considerable fraction of the empirical literature has examined this issue (referred to as market power).

In Chapter 2 we have tested whether certain price and volume trends could be observed on the real-time markets that were consistent with the market system (i.e. merit-order) that was imposed by the regulator. In Chapter 4 we have modelled the prices that we observe on several international day-ahead markets, using an econometric model that is consistent with the market microstructure of this particular type of spot market. Hence, in both Chapters we answer research questions, which essentially stem from the way the spot markets have been designed by the decision-makers (regulators and governments). Other questions on market design that has not been resolved yet are for instance the question whether the deregulated markets are structured in such a way that the power firms have the incentives to continue to invest in the supply security (e.g. California crisis stems from poor market structure). The stochastic day-ahead price models that have been introduced in Chapter 3 and 4 can be further explored, for instance by examining the forecasting performance of these models. Knittel and Roberts (2005) claim that models that include factors to control for weather effects (next to the factors that control for seasonal and mean-reverting behavior in traditional models (e.g. equation A3.2)) perform rather well. However, they do not conduct out-of sample tests to substantiate this claim. Hence, it would be interesting to investigate the forecast power of next-day weather forecasts for predicting power prices observed on the day-ahead markets (NB: the literature on weather forecast and electricity sales is well-documented). The ongoing deregulation has also triggered the incentive among players that are active on the international energy markets to study the opportunities of cross-hedging on their power portfolio (such as the portfolio discussed in chapter 6). Such a hedge involves entering into opposite forward contracts in two distinct but spot price correlated markets, and reselling on the spot markets on of these markets during the delivery period of the forward contract. The objective of a cross-hedge is that anytime the marketer enjoys (suffers) a profit (loss) on his portfolio position in one market, this is (partially) offset by the loss (profit) encountered on the spot-forward position in the other market. Questions that have not been resolved yet are: Is the market (let's say the European markets examined in this thesis) complete enough to erode the benefits of a cross-hedge? Could an international investor build up an almost perfect hedge for his power portfolio by using one market as a reference point (wheelspinning market)? What imposes risk premiums in one market to be different from other one? Why would spot price forecasts in one market be different from other market? Prior research fails to provide a satisfactory empirical framework to describe the cross-hedge opportunities in power markets (Woo et al, 2001). We could build upon the cross-hedge theorem introduced by Anderson and Danthine (1981), and use the the Fama (1984) framework discussed in Chapter 5 to disentangle risk premiums and spot price expectations from the forward basis observed in the cross-hedge markets.

7.3 Reflection

It is noted that the findings in this thesis are subject to certain limitations. The generalisation of its findings is reduced by the use of a relatively small sample size in empirical studies presented in this thesis. The small sample size is caused by the recent deregulation of the power markets, and the limited (public) availability on market data.
A serious limit in Chapter 2 is that we on one hand do not (attempt to) measure the change in market efficiency, while on the other hand we argue that we observe a trend in the market that goes in line with what we would expect from increased market efficiency. The research method proposed in Chapter 3, along we show that the Student-t distribution is capable of correctly capturing the fat-tailed behaviour of electricity prices should be regarded as a diagnostic test. Therefore, the results are only preliminary (but not conclusive) evidence that our proposed method is a candidate to model the non-normal behaviour of electricity prices in addition to other models such as jump diffusion models or switching regimes models. Furthermore, the research design employed in the panel data study (Chapter 4) has not provided a way to control for seasonality and price shocks. The results reported in Chapter 5 and 6 are conditional to the assumptions being made on price- or investor behavior, which are common in finance studies (representative investor, mean-variance optimizer and so forth).

Recently, techniques have been introduced in statistics, commonly referred to as functional data analysis (Ramsay and Silverman, 1997), that treat observations as functions rather than values (in classical methods, variation in an observed variable is attributed to other observed variables). These extensions to the classical statistical methods employed in this Thesis can provide additional insights, for instance when the data is highly dimensional (e.g. when price data would be not equally spaced). Finally, the fact that market structure differs substantially across markets, makes it difficult (caution should be exercised) to generalize the documented evidence to other markets than those studied in this Thesis.

Nederlandse samenvatting (Summary in Dutch)

Electriciteit heeft een aantal unieke kenmerken die haar doen verschillen van andere energie producten zoals olie en gas, waarvan onze economie afhankelijk is. Zo is er geen volwaardig substituut voor electriciteit, hetgeen de de geringe prijselasticiteit van de vraag verklaart. Daarnaast zijn er geen mogelijkheden om electriciteit op te slaan wat tot gevolg heeft dat er continu evenwicht tussen vraag en aanbod dient te bestaan. Electriciteit dient dus nadat het geproduceerd is direct geconsumeerd te worden. Omdat het verbruik van electriciteit door consumenten grillig is, bijvoorbeeld door weersinvloeden en door variaties in het consumptiepatroon, speelt het tijdsapect een cruciale rol in de waardering van het product electriciteit. Een andere belangrijke factor in de waardebepaling is dat de flexibiliteit om snel in te spelen op vraagveranderingen per type productiecentrale (gebaseerd op type brandstof: fossiel, nucleair, water) verschilt. Zo zijn de productiekosten van electriciteit afkomstig uit fossiele centrales relatief hoog (in vergelijking met nucleaire centrales), maar daarentegen kunne ze relatief snel worden ingeschakeld naar hogere capaciteitsniveau's om bijvoorbeeld op piekvraag in te spelen. Electriciteit geleverd op elk tijdstip of over verschillende perioden wordt daarom beschouwt als een apart product.

Traditioneel werden stroomprijzen bepaald door de toezichthouder van het stroomnetwerk of werd stroom verkocht op basis van bilaterale contracten tussen centrales en energiedistributiebedrijven die de stroom doorverkochten aan klanten. Toen waren prijzen vrijwel constant, en daarom speelden genoemde karakteristieken geen rol van betekenis in het prijsproces. Nu echter wel. Sinds 1990 hebben verschillende landen wereldwijd, elk in hun eigen tempo en fasesysteem, hun electriciteitsindustrie gedereguleerd: Verschillende electronische beurzen zijn gecreëerd met een vaak op elkaar aanluitende beleggingshorizon, wat het mogelijk maakt om vraag en aanbod tot op zeer korte termijn (half uur of tot op het kwartier) bij elkaar te brengen. Hier worden biedingen gedaan door bijvoorbeeld producenten of handelaren voor stroomlevering in een toekomstige periode die afhangt van de beleggingshorizon van de beurs. Deze biedingen worden gekoppelt met geplaatste inkooporders. De wet van vraag en aanbod bepaalt dus tegenwoordig de stroomprijs.

Het moge duidelijk zijn dat de door de introductie van marktwerking, de stroomprijzen voor onmiddelijke levering (de zogenaamde spotprijzen) vanwege de afwezigheid van stroomvoorraden die als buffer kunnen dienen voor mismatches tussen vraag en aanbod, gekarakteriseerd worden door onder meer plotselinge schokken en tijdsafhankelijke schommelingen. De mate van deze fluctuaties zien we niet terug in spotprijzen op andere commoditeitsmarkten of financiële markten. De noodzaak voor marktparticipanten om zich middels de handel in korte-, middellange-, en langetermijncontracten tegen het uniek hoge spotprijsrisico te beschermen, en daarmee de leveringsverplichting op overeenkomstige investeringshorizon af te dekken, is evident. De afgelopen jaren zijn een scala van deze termijncontracten op de electriciteitsbeurzen geïntroduceerd, ook wel derivaten genoemd. 'Derivaat' betekent 'afgeleide', en de waarde van een dergelijk contract is afgeleid van een onderliggend instrument. In het geval van forwards (bilateraal contract), futures en opties (beiden beurscontracten), de bekendste type derivaten, is dit het spotprijsproces. Een belangrijke functie van derivaten is dat de handel hierin de mogelijkheid biedt om spotprijsrisico te reduceren of te elimineren. Deze activiteit wordt hedgen genoemd.

Derivaten voor de meeste onderliggende instrumenten, zoals bijvoorbeeld graantermijncontracten (graantermijncontracten worden sinds de 18e eeuw verhandelt), kennen een lange historie. Dit geldt eveneens voor de 'cost-of-carry' theorie ontwikkeld in de jaren 1930 door gerenommeerde economen zoals Keynes om bijvoorbeeld futures en forwards te waarderen, of de optieprijstheorie van Black en Scholes uit 1972, welke hen een kwart eeuw later de Nobelprijs opleverde. In beide waarderingsmodellen wordt verondersteld dat het onderliggende instrument opgeslagen kan worden, hetgeen niet geldt voor electriciteit. Daarnaast maken de genoemde spotprijskarakteristieken van electriciteit, het repliceren van het derivaat in termen van het onderliggende spotprijsproces geen eenduidige exercitie, hetgeen veelal wèl het geval is voor derivaten op andere onderliggende instrumenten zoals olie, gas, goud, aardappelen, aandelen of obligaties. Repliceren wil zeggen dat stroomderivaten handelaren hun portfolio risiconeutraal ('risicovrij') kunnen maken door het innemen van derivaten aan de ene kant, en aan de andere kant (de replicatiestrategie) het (ver)kopen en vervolgens vasthouden van de onderliggende hoeveelheid stroom tot de in het derivatencontract vastgelegde periode waarop stroomlevering moet plaatsvinden (hetgeen ook gedaan wordt om zo de positie te sluiten). Door de afwezigheid van opslagmogelijkheden voor stroom kan dit echter niet.
We kunnen concluderen dat we niet zomaar kunnen vertrouwen op de traditionele theorie, wanneer het gaat om het modelleren van electriciteits spotprijzen en het waarderen van stroomderivaten. Het verkrijgen ven inzicht in spot -en derivatenprijzen en het beheren van een portfolio van deze contracten over de tijd heen (ook wel portfoliomanagement genoemd), vormt daarom de motivatie van de studies die in dit proefschrift zijn gebundeld.

Vanwege de korte historie van stroomspot- en derivatenmarkten is het aantal empirische studies relatief klein. Het grootste gedeelte van het empirisch werk moet nog gedaan worden. We leveren een bijdrage aan de empirische literatuur door het formuleren en toetsen van niet eerder geteste hypothesen, het aandragen van alternatieve methodologiëen voor prijsmodellering, en we laten zien hoe traditionele prijs, -en portfolio theorie met de juiste aanpassingen kan worden toegepast in electriciteitsmarkten.
Het onderzoek bestaat uit empirische studies waarin tijdreeksanalyse, extreme waardetheorie en paneldatamethodologie wordt toegepast om daarmee alternatieven of toevoegingen aan te dragen naast de traditionele spotprijs-, derivatenprijs-, en portfoliomanagement theorie. Data is verkregen van vier van de zes meest actieve stroomderivatenbeurzen wereldwijd: de Nordic Power Exchange (NPX), European Energy Exchange (EEX), Amsterdam Power Exchange (APX) en Paris Power Exchange (PPX).

Modelleren van electriciteits spotprijzen
Day-ahead beurzen en real-time beurzen, ook wel onbalansmarkten genoemd, spelen een cruciale rol in het goed functioneren van een onbalanssysteem in de huidige geliberaliseerde electriciteitsmarkt. Een beperkt aantal studies heeft zich bezig gehouden met het prijsverschil tussen beide beurzen. Sommige studies schrijven dit prijsverschil toe aan consumptiegerelateerde factoren (Longstaff en Wang, 2004). Anderen richten zich op de mogelijkheden die dit prijsverschil biedt om hieruit winst te behalen, bijvoorbeeld door het herkennen en vervolgens implementeren van winstgevende stroominkoopstrategiëen (Boogert en Dupont, 2005). Wij echter, onderzoeken of de electriciteitsmarkt efficiënter is geworden, door de te verwachten trend van genoemd prijsverschil toe te schrijven aan

efficiëntietoename (als gevolg van de liberalisatie). Zoals bekend is de vergroting van de efficiëntie de belangrijkste doelstelling van het EU beleid om tot een vrije interne energiemarkt te komen. Door de liberalisering van de energiemarkt worden lagere prijzen verwacht als gevolg van verbeterde concurrentie en een efficiënter gebruik van grondstoffen en productiecapaciteit.

Hoofdstuk 2 toont de resultaten van een onderzoek naar de veranderingen in efficiëntie van de Nederlands electriciteitsmarkt. We onderzoeken de historische ontwikkeling van genoemd electriciteitsprijsverschil, en de stroomprijs- en stroomvolumetrend op de zogenoemde onbalansmarkt. Omdat het verbruik van electriciteit door consumenten grillig is, zijn er twee markten waarop energiebedrijven electriciteit op de korte en zeer korte termijn kunnen inkopen: De APX en de onbalansmarkt. Op de APX kan stroom worden verkocht die de volgende dag wordt geleverd in een specifiek uur. De onbalansmarkt kent een beleggingshorizon van slechts 15 minuten, en deze beurs wordt gebruikt om korte termijn tekorten en -overschotten glad te strijken. In veel EU-landen is de transmissie systeem operator verantwoordelijk voor de balansactiviteiten op het landelijke stroomnetwerk. In Nederland is dat TenneT. Alle bedrijven die aangesloten zijn op het electriciteitsnet dienen bij TenneT energieprogramma's in te leveren. Hierin staan de verwachte consumptie van stroom en levering van stroom aan het net voor elk kwartier van de dag. Deze verantwoordelijkheid kan worden uitbesteed aan een door TenneT erkende programmaverantwoordelijke. Onbalans ontstaat wanneer TenneT een verschil tussen de gerapporteerde en werkelijk geconsumeerde of geleverde hoeveelheid stroom constateert. In situaties van negatieve (positieve) onbalans koopt (verkoopt) TenneT stroom van (aan) producenten via de onbalansmarkt en verrekend deze prijs met de veroorzaker van de onbalans. In de economische literatuur wordt een markt als allocatief efficiënt beschouwd wanneer elke inkooporder met die overeenkomstige bieding geconfronteerd (waaruit de marktprijs ontstaat) wordt die afkomstig is van de producent met de laagste marginale kostenstructuur; zie o.m. Smith (1962) voor een uiteenzetting.
Sinds het baanbrekende werk van Smith zijn talrijke welvaartsstudies verschenen die geliberaliseerde markten bestudeerden. De studies hebben vaak onoverkomenlijke problemen met elkaar gemeen betreffende de validiteit en beschikbaarheid van de data: allocatieve efficiëntie verbeteringen zijn nu eenmaal lastig te kwantificeren (zie onder meer Boles de Boer en Evans, 1996). Alhoewel onze studie niet direct allocatieve efficiëntie meet en niet de gehele markt beslaat, kunnen we een verandering in de allocatie van centrales zien, door de dynamiek van APX en onbalans te analyseren. Op de APX geven aanbieders van stroom aan welke volume zij bereid zijn te leveren tegen verschillende prijzen. Het op de APX aangeboden volume neemt alleen toe als de prijs stijgt tot boven het niveau van de kostprijs van de eerstvolgende electriciteitscentrale die tegen die prijs bereid is te leveren, enzovoorts. De volgorde waarin de verschillende centrales worden ingezet, de zogenoemde merit-order, zorgt ervoor dat dat de producent die tegen de laagste kosten stroom kan produceren het grootste volume afzet. In een efficiënte stroommarkt produceren de goedkoopste centrales het meest.
Dure centrales zullen alleen produceren als er veel vraag naar stroom is (Wolfram, 1999). Aangezien de goedkoop producerende centrales al ingezet zijn als gevolg van de merit-order op de APX, zullen alleen de dure centrales nog capaciteit beschikbaar hebben.

Onze eerste hypothese luidt dan ook dat naarmate de markt allocatief efficiënter wordt de onbalansprijzen toenemen. Voor de liberalisering kocht TenneT immers de stroom in tegen een gewogen gemiddelde kostprijs (gewogen naar geïnstalleerde productiecapaciteit). Merk op dat doordat we tevens onderzoeken of het prijsverschil tussen APX en onbalansmarkt een positieve trend laat zien, we impliciet rekening houden met prijstoenames in de brandstofmix van producerende centrales die actief zijn op beide beurzen. De tweede hypothese heeft betrekking op de onbalansvolumes, en toetst of de volumeverandering overeenkomt met de trend die je zou verwachten bij een hogere mate van efficiëntie. In een geliberaliseerde markt zullen de onbalansvolumes dalen omdat energiebedrijven het risico van prijsschommelingen op de onbalansmarkt willen beperken. Hiermee wordt de prikkel vergroot om efficiënter het verbruik van hun klanten te voorspellen. Daarnaast is inzicht in de dynamiek van onbalansvolumes belangrijk omdat een dalende trend in onbalansvolume resulteert in minder schokken in het balanssysteem. Zolang de door TenneT bepaalde minimale hoeveelheid reservecapaciteit is gegarandeerd, verbetert hierdoor de leveringszekerheid van electriciteit.
De in hoofdstuk 2 gerapporteerde resultaten laten duidelijk een significant positieve trend zien van de onbalansprijzen en het prijsverschil tussen APX en onbalansmarkt, terwijl de onbalansvolumes significant zijn gedaald. We concluderen dat de Nederlandse electriciteitsmarkt efficiënter is geworden.

Hoofdstuk 3 concentreert zich op het modelleren van het gedrag van dagelijkse basislast day-ahead stroomprijzen. Zoals gezegd, worden op verscheidene day-ahead beurzen prijzen gequoteerd voor stroomlevering op een specifiek uur van de volgende dag. Het dagelijks gemiddelde is dan de gemiddelde prijs over 24 uur, ook wel basislast uren genoemd. De prijsdynamiek van deze gemiddelde prijzen is van groot belang, omdat deze prijsserie wordt gebruikt als referentiepunt van zogenaamde marking-to-market waarderingen, en kan dienen als basis voor optiecontracten zoals callable opties.
Verscheidene studies laten zien dat deze day-ahead prijzen over de tijd heen gedrag vertonen zoals mean-reversion(de tendens van een prijs om na een schok weer terug te keren naar het lange-termijn gemiddelde), seizoensafhankelijkheid en plotselinge schokken. In eerste instantie werden prijsmodellen geïntroduceerd die mean-reversion, en seizoensinvloeden van day-ahead prijzen beschreven; zie o.m. Pilipovic (1998). Maar al gauw richten studies zich op het modelleren van de frequente prijsschokken die day-ahead prijzen zo kenmerken, zoals Deng (1999) en meer recent Huisman en Mahieu (2003). In deze studies worden zogenaamde jump diffusie procesmodellen (Deng), en switching regime modellen (Huisman en Mahieu) geïntroduceerd voor het modelleren van extreme prijsbewegingen, waarbij het derde moment (skewness: geeft indicatie van de mate van symmetrie rond het gemiddelde van de verdeling) en vierde moment (kurtosis: geeft indicatie van de staartdikte van de verdeling) van de prijsverdeling direct wordt meegenomen. Het voordeel van deze methoden is dat ze dus naast het beschrijven van de prijsschokken, ook prijsgedrag kunnen beschrijven dat afwijkt van de in statistiek gehanteerde normaliteit veronderstelling van de ruisterm; de ruisterm in het prijsmodel wordt veelal normaal verdeelt of tenminste IID verondersteld. Helaas zijn genoemde methodieken niet eenvoudig toepasbaar, zoals het switching regime model welke vanwege de niet direct observeerbare regimes, de schattingen van meerdere parameters omvat. We richten ons op de staartverdeling van de ruisterm van een day-ahead prijsmodel en we passen extreme waarde theorie toe om de staart-index, een expliciete maatstaf voor de

staartdikte te schatten. We willen weten of de extreme waarde theorie geschikt is om, net als jumpdiffusie-, en switching regime modellen, extreme prijsbewegingen te modelleren. Het voordeel van het toepassen van extreme waardetheorie op de ruisterm is dat we direct de extreme prijsschommelingen kunnen beschrijven, zonder dat we ons druk hoeven te maken over de karakteristieken van de gehele verdeling. Dikke staarten, althans dik t.ov. de staarten van de normale verdeling, reflecteren een hogere kans dat extreme prijsbewegingen voorkomen. Dit betekent dat marktparticipanten te maken krijgen met hoger dan 'normaal' risico. Toch wordt de normaliteitveronderstelling gemakshalve toegepast in Monte Carlo prijs simulaties, -en derivatenprijsmodellering, hetgeen kan leiden tot onderschatting van de werkelijke hoeveelheid prijsrisico die marktparticipanten kunnen tegenkomen. We stellen de Student-t verdeling als alternatief voor, temeer omdat deze verdeling makkelijk geparameteriseerd kan worden door de op extreme waardetheorie gebaseerde staartindex.
In de literatuur zijn er vele staartindexen geïntroduceerd, waarvan degene door Hill (1975) de bekendste is. De staartindex is een maat voor de staartdikte van de verdeling (in ons geval de verdeling van de ruisterm van een stroomprijsmodel): Hoe dikker de staart, hoe groter de kans op een extreme prijsbeweging, hoe lager de snelheid waarmee de index naar nul beweegt, en des te lager de waarde van staartindex. We passen de staartindex toe van Huisman e.a. (2001) (hierna HKKP schatter), omdat deze in tegenstelling tot andere staartindex schatters zoals de Hill staartindex, wèl corrigeert voor afwijkingen in kleine steekproeven. Zie Pictet (1996) een uitstekend overzicht van diverse staartindex schatters. Merk op dat door de korte historie van geliberaliseerde stroommarkten kleine steekproeven van day-ahead stroomprijsseries inherent zijn, hetgeen het gebruik van de HKKP schatter aantrekkelijk maakt. De methode die we in hoofdstuk 3 voorstellen om extreem stroomprijsgedrag op de APX beurs te beschrijven is eenvoudig in drie stappen te implementeren: (1) middels niet lineaire kleine kwadratenmethode schatten we de parameters van een day-ahead prijsmodel zoals gebruikt in Lucia en Schwartz (2002) en Mahieu en Huisman (2003). De prijs is hier de som van een deterministische- en stochastische component, die respectievelijk voorspelbare trends en mean reversion modelleren. (2) Vervolgens wordt de HKKP index geschat op de ruis term verdeling, en wordt deze index gebruikt om de Student-t verdeling te parameteriseren. Een groot voordeel van de Student-t verdeling is namelijk dat de vrijheidgraden parameter, welke de vorm van deze symmetrische verdeling bepaalt, direct gerelateerd is aan de staartdikte van de verdelingsfunctie. We tonen de resultaten van een zogeheten goodness-of-fit test die aantoont dat de ruis term wel beschreven kan worden met de Student-t verdeling, maar niet door de normale verdeling. (3) Tenslotte tonen we middels Monte Carlo simulaties aan (welke vaak gebruikt worden in risicomanagement technieken als Value-at Risk), dat wanneer we willekeurige innovaties trekken uit een Student-t veronderstelde ruis verdeling, het gesimuleerde prijsproces de werkelijke APX tijdreeks benaderd. We laten zien dat dit niet het geval is wanneer we de normale verdeling zouden hanteren. We kunnen dezelfde conclusie trekken op basis van de gerapporteerde skewness- en kurtosis schattingen voor beide prijsprocesssen. We claimen dat de gepresenteerde methodologie een eenvoudig te implementeren methodiek is om niet-normaal prijsgedrag goed te beschrijven, naast de jump diffusie en switching regime modellen.

In hoofdstuk 4 wordt, net als voorgaand hoofdstuk, het prijsgedrag van de day-ahead markt nader belicht. Alleen ditmaal richten we ons niet op het gedrag van de dagelijkse gemiddelde prijzen, maar op de afzonderlijke uurprijzen die gequote worden voor stroomlevering op de volgende dag. Veel markten onderscheiden dagelijks gemiddelde basislast prijzen en gemiddelde pieklast prijzen. Laatstgenoemde prijzen worden gemiddeld over door de beurs gedefinïeerde piekuren, welke in het algemeen de uren gedurende werkkdagen betreft wanneer de economische activiteit hoog wordt verondersteld. De modellen ontwikkeld voor dagelijks gemiddelde prijzen (voor een overzicht: zie Bunn en Karakatsani, 2003), kunnen niet direct gebruikt worden om inzicht te krijgen in uurprijsdynamiek. Neem bijvoorbeeld het geval dat uurprijzen bewegen rond een uurspecifiek gemiddelde ('mean-reversion'). Dan zal een prijsmodel met een dagelijks gemiddelde niet voldoen. Men kan zich afvragen of volatiliteitstructuur en/of het niveau van mean-reversion constant over de dag is of varieert per uur. En hoe zit het eigenlijk met het correlatiepatroon tussen verschillende uren? Deze vragen zijn relevant omdat veel agenten in day-ahead markten blootgesteld worden aan schommelingen in uurprijzen. Electriciteitsproducenten laten hun nominatie schema's afhangen van de verwachte prijzen voor stroomprijslevering gedurende de volgende dag. Ondernemingen die stroom consumeren volgens een patroon dat niet kan worden afgedekt met standaard basislast en pieklast contracten, zullen behoefte hebben aan contracten die leveren op enkele uren van de dag. Om deze contracten te waarderen, kunnen market makers niet alleen vertrouwen op dagelijkse gemiddelde prijzn, maar zullen ook inzicht moeten hebben in verwachtingen en risico's behorend bij specifieke uurprijzen.

Enkele studies hebben de noodzaak aan het modelleren van uurpijsdynamiek onderschreven. In de eerdergenoemde studie van Saravia (2003), wordt het prijsverschil tussen day-ahead en real-time uurprijzen toegeschreven aan marktmacht en speculatieactiviteiten. Longstaff en Wang (2004) bestuderen eveneens genoemd prijsverschil (zij noemen dit de day-ahead risicopremie) in de Amerikaanse markt, en relateren dit aan consumptiefactoren (zoals vraag, omzet). Zij specificeren een zogenaamd Vector Autoregressie (VAR) systeem voor elk van de 24 uur, waarbij genoemde ex-ante consumptiegerelateerde risicomaatstaven de verklarende variabelen voor onverwachte prijsveranderingen zijn. Op deze manier proberen ze inzicht te verschaffen in uurprijsdynamiek. Wolak (1997) concenteert zich op uurprijsdynamieken in verscheidene stroommarkten wereldwijd. Hij past zogenaamde principale componenten analyse toe op de covariantie matrix van de ruisterm, verkregen uit een VAR systeem van (half) uur prijzen. Wolak's bevindingen tonen aan dat soms wel meer dan 20 risicofactoren nodig zijn om 90% van de prijsvariatie te kunnen verklaren.

In genoemde studies, worden uurprijzen soms elk apart gemodelleerd of wordt soms een correlatiepatroon tussen de uren verondersteld. Anderen 'stapelen' de uurprijzen en passen methodieken toe alsof het een tijdreeks betreft. Een belangrijk verschil tussen het modelleren van dagelijkse gemiddelde day-ahead prijzen en het modelleren van day-ahead uurprijzen is dat uurprijzen echter niet gezien kunnen worden als een puur tijdreeksproces. Tijdreeks modellen veronderstellen namelijk dat de informatie set wordt geupdate wanneer we van een observatie naar de volgende observatie gaan in de tijd. Deze veronderstelling is echter niet geldig voor uurprijzen aangezien de markt microstructuur van day-ahead markten niet voorziet in de mogelijkheid tot continue handel. Op veel day-ahead markten leveren agenten hun 24-uurs biedschema rond het middaguur; uurprijzen worden dus vastgesteld op hetzelfde moment. Daarom kan men voor het bestuderen van uurprijsdynamiek niet zomaar vertrouwen op een tijdreeksbenadering, zoals gedaan wordt in sommige eerdergenoemde studies.

In dit hoofdstuk stellen we voor om uurprijzen te modelleren middels een paneldata raamwerk, welke wèl perfect bij de microstructuur van day-ahead markten. Paneldata modellen beschrijven de dynamieken van een cross-sectie van individuen over de tijd heen (eerste dimensie), en zijn veelvuldig toegepast in de financiële literatuur. Merk op dat de stroomuurprijzen gezien kunnen worden als cross-sectionele individuen, omdat prijzen gequote worden op hetzelfde moment. De tweede dimensie van een panelraamwerk, de tijdsdimensie, ondervangt de dagelijkse prijsdynamiek die onstaat doordat de day-ahead markt dagelijks 24 prijzen quote. We schatten de parameters van een algemeen paneldatamodel dat bestaat uit een deterministische- en stochastische component, die respectievelijk voorspelbare trends en mean reversion modelleren. Merk op dat dit generieke model, in essentie hetzelfde model is als geïntroduceerd in hoofdstuk 3. Alleen nu wordt het model geschat op uurdata, welke wordt verkregen van drie Europese day-ahead markten: de APX, EEX en PPX. Naast het algemene model worden er drie panelmodel varianten geïntroduceerd, waarbij óf de uurspecifieke gemiddelde parameter, óf de uurspecifieke mean-reversie parameter, óf beiden worden gerestricteerd. Merk op dat in de laatstgenoemde variant, de paneldata dimensie alleen tot uitdrukking in de covariantiematrix van de ruisterm. Merk op dat deze matrix belangrijke informatie bevat voor een handelaar, omdat ze hieruit kan aflezen hoe haar bieding voor levering van stroom op uur h in de volgende dag afhangt van de 'omliggende' uren op het moment van de bieding. Op basis van de resultaten van een modelspecificatie test, concluderen we dat zowel het algemene model als de variant op dit model met een uurspecifieke parameter voor de gemiddelde prijs maar met een constante mean-reversie parameter, de uurprijsdynamiek het beste beschrijven.
De resultaten die we in hoofdstuk 4 presenteren, laten duidelijk zien dat uurprijzen in day-ahead markten, bewegen rond een uurspecifiek gemiddelde, en dat ze terugkeren naar hun gemiddelde met een snelheid, de zogenaamde mean-reversion rate, die per uur verschilt. Zo laten de super pieklast uren van 18 uur tot 20 uur veel minder mean-reversion zien. Dit is te verklaren door de hogere vraag in deze uren, welke leidt tot minder beschikbare reservecapaciteit met als gevolg een toenemende kans tot prijspieken. Dit betekent dat de waarde van derivaten die leveren in super pieklast uren, niet gebaseerd dienen te worden op modellen die gebruik maken van basislast en/of pieklast derivaten, aangezien deze prijzen de werkelijke mate van mean-reversion overschatten. Wat verder opvalt is dat er een blokstructuurachtige cross-sectioneel correlatiepatroon tussen de uurprijzen valt waar te nemen. Prijzen in pieklast uren correleren sterk met elkaar, en datzelfde geldt voor de correlatie tussen basislast uren. Dit effect kan verklaart worden door verschillen in de reservecapaciteit tussen de twee blokken. De lagere reservecapaciteit in de pieklast uren, betekent dat de prijzen in deze uren meer prijsschommelingen vertonen dan prijzen in de uren buiten de pieklast om.
Toepassingen van de in dit hoofdstuk gepresenteerde panelmethodologie om uurprijzen te modelleren kunnen gevonden worden in electriciteits risicomanagement, contract structurering, en stroomderivatenwaardering. Zo worden er momenteel worden uurprijsopties in de Amerikaanse markten verhandeld.

Modelleren van electriciteits futures-, en forwardprijzen
In hoofdstuk 5 besteden we aandacht aan het klassieke issue hoe futures-en forward prijzen en spotprijzen met elkaar gerelateerd zijn. Alhoewel forward- en futurescontracten in een aantal opzichten sterk van elkaar verschillen hebben ze een belangrijk kenmerk gemeen;

het onderliggende prijsproces is de belangrijkste verklarende variabele voor de vaststelling van de waarde van het (forward of futures) contract (Geman, 2005). Daarom maken we geen onderscheid tussen beide in dit proefschrift wanneer we ingaan op futures -en forwardprijzen. Hierna spreken we gewoonweg over futuresprijzen. Zoals gezegd kan de cost-of-carry relatie niet worden toegepast om risiconeutrale electriciteits futures prijzen af te leiden uit onderliggend spotprijsproces. Om toch spot- en futuresprijzen gelijktijdig te modelleren wordt veelal de prijsmethodologie uit de rentestructuur-, of opslaanbare goederen literatuur toegepast. Zo wordt het risconeutrale prijsproces verklaart in termen van rente-, opslag-, en conveniencekosten, of risicopremies. Men construeert dan een theoretische futurescurve geconstrueerd, die overigens in het algemeen niet overeenkomt met geobserveerde prijzen. Voorbeelden zijn te vinden in Deng (1999) en Lucia en Schwartz (2002). Anderen, zoals Clewlow en Strickland (1998) en Koekebakker en Ollmar (2005), nemen juist de futures curve geobserveerd in de markt als gegeven, en leidden middels arbitrage-, of 'faire'-waarde principes derivatenprijzen af. In onze studie nemen we de geobserveerde futuresprijzen ook als gegeven. We definiëren de futuresprijs als de som van twee componenten: de verwachte spotprijs over de leveringsperiode, en de risicopremie. We zijn niet zozeer geïnteresseerd in het afleiden van 'faire' of risiconeutrale waarden voor futures, maar concentreren ons op de vraag in hoeverre futuresprijzen gezien kunnen worden als voorspeller van spotprijzen, en risicopremie. Deze twee componenten worden uitgedrukt in percentages van de basis van het futurescontract. Dit is het prijsdifferentieel tussen de futures -en spotprijs geobserveerd op dezelfde dag.

We volgen het model van Fama (1984) voor gezamenlijke schatting van de voorspellings- en premie component in futuresprijzen. Dit model, dat in Fama is toegepast om inzicht te krijgen in de opbouw van futuresprijzen in de wisselkoersmarkt, en is in Fama en French (1987) gebruikt om de voorspelkracht en risicopremies in commodityfutures te verklaren. Om inzicht te krijgen in de ontwikkeling van de voorspelkracht en risicopremie over de tijd heen, schatten we de modelparameters die de verklarende waarde van beide componenten reflecteren op marktdata van contracten met elk hun eigen beleggingshorizon. Zo krijgen we schattingsresultaten van de dataset van contracten die stroom leveren in de basislast *eerst*volgende maand na het moment van observatie (kortweg M1 contracten), in de *tweede* maand na het moment van observatie (M2 contracten), enzovoort. De theorie geïntroduceerd door Samuelson (1965) geeft ons enige houvast wat we kunnen verwachten: Hij toont aan dat wanneer het onderliggende spotprijsprocess mean-reverting is, de volatiliteit van het futureprijs rendement, toeneemt naarmate het contract dichter bij de expiratiedatum komt. Inmiddels is in verschillende commodity markten (opslaanbare energie-, metaal-, agriculturele goederen) het Samuelson effect in meerdere of mindere mate waargenomen (voor een overzicht: zie Bessembinder e.a., 1996). Wanneer de beleggingshorizon van het contract langer is, wordt ook wel gesproken over een toename van de 'time-to-maturity' van het contract.[64]

Voor de empirische analyse gebruiken we data van de Nederlandse en Duitse markt, respectievelijk: APX voor spotdata en ENDEX (European Energy Derivatives Exchange) M1, M2 en M3 forwarddata. En de EEX voor M1 tot M6 futuresdata. We gebruiken alleen maandelijkse data, dat wil zeggen: noteringen op de eerste handelsdag van de maand. We

[64] Forward-, en futures contracten kennen ook verschillende lengte van leveringsperioden (bijvoorbeeld maand, kwartaal, jaar). In deze studie richten we ons op maandcontracten, omdat dit veruit de meest liquide contracten zijn.

leveren bewijs dat de grootte van de risicopremie component in de basis significant toeneemt naarmate de time-to-maturity van het contract afneemt, hetgeen betekent dat de prijs van electriciteitsderivaten een trend laat zien die overeenkomt met het time-to-maturity patroon beschreven door Samuelson. Tegelijkertijd zien we een significant stijgende trend in het percentage dat de voorspellingscomponent uitmaakt van de forward- en futures basis, naarmate de beleggingshorizon (time-to-maturity) langer wordt. De gevonden resultaten zijn consistent met de 1-factor-, en 2-factor mean-reverting stroomprijsmodellen die Lucia en Schwartz (2002) gebruiken om NPX spot -en futures prijzen te modelleren. We laten zien dat uit hun modellen, de negatieve relatie tussen de grootte van de risicopremie component en de time to maturity direct kan worden afgeleidt.

Vervolgens passen we dezelfde analyse toe, alleen ditmaal gebruiken we dagelijkse prijsdata van M1 contracten. We willen namelijk meer inzicht krijgen in het issue van prijsconvergentie. Volgens de literatuur convergeert de prijs van een derivaat naar de spotprijs van het onderliggend instrument, op het moment dat de we heel dichtbij de dag van expiratie van het derivaat komen (zie Hull, 2002). Een simpel voorbeeld kan dit duidelijk maken. Laten we de arbitragemogelijkheden (de kans om een risicovrije winst te behalen door bepaalde derivatenpositie in te nemen) van een handelaar bekijken in de volgende twee scenarios: (i) de forward-, of futureprijs ligt boven de spotprijs *tijdens* de leveringsperiode van het futurescontract. (ii) de futuresprijs ligt onder de spotprijs *tijdens* de leveringsperiode van het futurescontract. De volgende strategie lijdt tot een risicovrije winst in (i), ook wel arbitragewinst genoemd: Verkoop het futurescontract, koop het onderliggend instrument en lever vervolgens het instrument aan de tegenpartij van het contract om zo de positie te sluiten. Merk op dat de tegengestelde strategie in (ii), de handelaar een arbitragewinst zou opleveren. Een belangrijk punt om te benadrukken is dat wanneer de prijsscenarios (i) en (ii) niet *tijdens* maar *voor* de leveringsperiode plaatshebben we de abitragestrategieën voor een onderliggend instrument als electriciteit opeens niet meer kunnen implementeren. Dit komt omdat we electriciteit niet kunnen opslaan, en dus geen manier hebben om het moment tussen (ver)koop en levering van electriciteit te overbuggen. De vraag rijst dus welke mechanisme spotprijzen en futuresprijzen met elkaar verbindt in electriciteitsmarkten. Voor dit deel van de empirische analyse gebruiken we dagelijkse data verkregen van de EEX markt en NPX markt, als input voor het Fama raamwerk. We rapporteren bewijs dat de risicopremie component in de M1 basis na een korte stijging in de eerste handelsdag geleidelijk aan daalt tot een niveau van 40% (60%) voor EEX basislast (pieklast) contracten en 20% voor NPX contracten, naarmate de handelsdag dichter bij de expiratiedag van het contract komt. Dit betekent dat de electriciteits futuresprijzen een patroon laten zien van geleidelijke (overigens niet perfecte) convergentie van de futureprijs naar de spotprijsverwachting toe.

De gedocumenteerde resultaten dragen op twee manieren bij aan het inzicht in het klassieke issue van de relatie tussen spot -en futuresprijzen in de derivatenliteratuur. Niet alleen tonen we aan hoe het time-to-maturity patroon verloopt in electriciteitsfutures. We laten ook zien hoe dit patroon verloopt voor de voorspellingswaarde -en risicopremies in electriciteitsfutures. De gevonden resultaten relevant voor handelaren en risico managers. Ze geven namelijk inzicht in de ontwikkeling van risicopremies, en in het maken van spotprijsverwachtingen. Een typische toepassing van onze resultaat is het vaststellen van gemiddelde prijsniveau's in Monte-Carlo simulaties. Een fractie van de futures basis kan dan gebruikt worden als voorspeller voor toekomstige prijzen, aangezien ze de marktverwachting van de verandering in day-ahead prijzen reflecteert.

Electriciteits portfoliomanagement
De liberalisatie van de energiemarkten heeft de de kosten-risico afweging die traditioneel bij de producenten en distributeurs ligt verplaatst naar de eindgebruiker. Voorheen was de energiewereld van de eindgebruiker eenvoudig: er was slechts 1 gereguleerde prijs, welke de (marginale) kosten van de productie-, transport- en distributieactiviteiten reflecteerden. Maar dit alles is dankzij de liberalisatie veranderd. De afnemer kan nu vrij kiezen. Blijft ze bij de huidige leverancier of niet? Koopt ze van tevoren electriciteit in tegen vaste prijs? En zo ja, hoevaak per jaar en hoever van tevoren? Om te kunnen profiteren van een lagere prijs of een beter aanbod, is dus een actieve houding van de afnemer vereist. Om zich in de markt staande te houden zal ze moet nadenken over haar consumptiepatroon en vervolgens een passende inkoopstrategie kiezen. Uit onderzoek van Van Damme (2005) blijkt dat met name de privéeindgebruikers een afwachtende hourding inneemt, en als ze al van leverancier wisselen ze even zo vaak kiezen voor een duurdere leverancier als voor een goedkopere. Maar ook de zakelijke gebruikers die meer van leverancier verandert (deels omdat hij prijsgevoeliger is), hanteren soms strategieën waarbij men zich kan afvragen of deze in lijn is met haar eigen risicopreferentie. Zo is de zogenaamde tender strategie, waarbij eens per jaar electriciteit van te voren wordt ingekocht een gebruikelijke strategie. Maar wat als blijkt dat een maand langer wachten aanzienlijker gunstiger had uitgepakt. Kan een onderneming dat eigenlijk wel veroorloven?
Eenzelfde kosten-risico afweging maken eindgebruikers echter al wel op de financiële markten: zo kiezen werknemers ervoor om een deel van hun pensioen tegen laag risico te beleggen, of kunnen mensen kiezen voor een passende ziektekostenverzekering.
Een conceptueel raamwerk dat veel in de financiële wereld gebruikt wordt om een kosten-risco afweging te maken is de zogenaamde Markowitz portfolio optimalisatie (voor een recente empirische toepassing portfolioprobleem bij pensioenspaarplankeuze werknemers, zie: Boyle e.a., 2006). Hier verwijst de term portfolio naar een combinatie (groep) van activa of bezittingen. De theorie ontwikkeld door Markowitz biedt de investeerder de mogelijkheid een portefeuille samen te stellen die overeenkomt met de gewenste hoeveelheid risico van de investeerder.
In hoofdstuk 6 richten we ons zo'n investeerder op de electriciteitsmarkt, en wel de eerdergenoemde eindgebruiker. Deze afnemer wenst zich te beschermen ('hedgen') tegen genoemd inkooprisico (kosten) door een portefeuille samen te stellen van spot -en derivatencontracten. We willen inzicht krijgen of de portfolio-optimalisatie theorie gebaseerd op het standaardwerk van Markowitz (1952), de eindgebruiker kan helpen in het selecteren van de voor optimale portefeuille. In algemene zin willen we dus weten of het Markowitz raamwerk, net als in vele andere markten, ook toepasbaar is in de electriciteitsmarkt. In Markowitz wereld zijn het verwachte rendement, en de standaarddeviatie van de portfoliorendementen betekenisvolle parameters voor het rendement en risico van de portfolio, en daarmee de twee citeria voor portfolioselectie. De door ons gehanteerde optimalisatiemethode is een variant op zijn raamwerk, omdat we niet de standaarddeviatie als risicomaatstaf gebruiken, maar een Value-at-Risk-*achtige* maatstaf. Value-at-Risk (VaR) deed in de jaren 1980 zijn intrede in de bancaire wereld, en werd oorspronkelijk gebruikt om de kredietwaardigheid van banken vast te stellen (voor een overzicht: Zie Jorion, 1997). Zo is de VaR-limiet voorgesteld door de Basel

Commissie van Bank Regulatie, vastgesteld als het maximaal verlies dat geleden wordt over een van te voren vastgestelde periode, éénmaal in de 100 gevallen mag voorkomen (kortweg 1% VaR).
Value-at-Risk neemt dus, in tegenstelling tot de standaarddeviatie, alleen de neerwaartse beweging ten opzichte van het gemiddelde mee, en dus niet de opwaartse beweging die als gunstig kan worden ervaren. Roy (1952) is de grondlegger van portfolio optimalisatie onder een dergelijke neerwaarts risicomaatstaf, welke de Markowitz' maatstaf vervangt. Sindsdien zijn verscheidene van deze portfolio optimalisatiemodellen geïntroduceerd (bijvoorbeeld Arzac en Bawa (1977), ook wel safety-first modellen genoemd, en ook empirisch getest zoals in Campbell e.a. (2001). In hun studie wordt de oplossing van het optimalisatieprobleem van een investeerder, gevonden in een vlak, gedefinieerd door de twee parameters gemiddeld rendement en VaR. Merk op dat in ons portfolio selectieprobleem geen portfoliorendementen maar portfoliokosten centraal staan, hetgeen betekent dat we onze oplossing vinden in een vlak gedefinieerd door een verwachte verwachte-kosten dimensie, en VaR-*achtige* dimensie. We spreken in onze studie van een Value-at-Risk *achtige* maatstaf, omdat het in onze studie dus draait om verwachte kosten en geen verwacht rendement, en daarom om opwaarts risico in plaats van neerwaarts risico. Een bijkomend voordeel ten favuere van het toepassen van VaR in het stroomportfolio selectieprobleem in vergelijking met de standaarddeviatie, is dat met deze maatstaf additioneel portfoliorisico meegenomen kan worden als gevolg van mogelijke niet-normale eigenschappen van de kostenverdeling (zie hoofdstuk 1 voor discussie niet-normaal verdeelde stroomprijsveranderingen).

Een beperkt aantal studies heeft zich beziggehouden met het eerder beschreven stroomportfolio selectieprobleem, waarbij moet worden opgemerkt dat we uitsluitend die studies bekijken die een statische[65] setting veronderstellen. (zodra de optimale combinatie contracten is bepaalt, kan hier op een later tijdstip binnen de beleggingshorizon niet meer van worden afgeweken) veronderstellen: Fleten e.a. (2000), en Vehviläinen en Keppo (2003), gebruiken respectievelijk een scenario-, en Monte Carlo raamwerk. We hanteren daarentegen het Markowitz raamwerk, dat middels een VaR achtige maatstaf is uitgebreid. Vehviläinen en Keppo, die eveneens de VaR maatstaf gebruiken voor de kwantificering van risico, claimen dat hun Monte Carlo-gebaseerde methode superieur is aan de Markowitz techniek, omdat deze de marktparticipant in staat stelt het selectieprobleem voor complexe portfolio's op te lossen. Echter, ze presenteren geen bewijs dat deze claim ondersteunt: zo testen ze hun model niet empirisch op uurdata maar weekdata, en veronderstellen ze geen stroomlast dynamieken maar een constante leveringslast, hetgeen wij daarentegen wel doen.

We beschikken over consumptieprofielen (stroomlastdata) van zakelijke eindgebruikers, spot-, en forwardprijsdata van de Nederlandse markt verkregen van respectievelijk TenneT, de APX en ENDEX. We passen portfolio theorie toe om voor zowel een constant als tijdsvariërend consumptiepatroon de efficiënte set van portfolio's te identificeren die

[65] Statisch houdt in dat zodra de optimale combinatie contracten is bepaalt, hier op een later tijdstip binnen de beleggingshorizon niet meer van kan worden afgeweken Het alternatief, een dynamische setting, impliceert dat electriciteitsspot -en derivatenbeurzen liquide zijn, om het herbalanceren van het portfolio mogelijk te maken. Dit is echter niet het geval in de huidige electriciteitsmarkt.

voldoen aan kosten-risicopreferentie van de marktparticipant. Wanneer we de ligging van de twee efficiënte grenslijnen met elkaar vergelijken, valt op dat de introductie van een variërend consumptieprofiel, het totale portfolio risico aanmerkelijk vergroot. We leveren empirisch bewijs dat optimale hedge ratio's zijn te identificeren, hetgeen betekent dat moderne portfolio theorie ook in electriciteitsmarkten kan worden toegepast. De in dit hoofdstuk voorgestelde portfolio optimalisatie benadering biedt een raamwerk om de risicopreferentie van de electriciteitsmarktparticipant te verbinden aan de keuze van stroom spot- en termijn contracten en is daarom een eerste stap naar de formulering van een strategische benchmark voor investeerders die hun portfoliomix willen managen over een bepaalde beleggingshorizon.

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Curriculum Vitae

Christian Huurman was born in Dacca (Bangladesh) on 10 May 1977. From 1995 to 2001, Christian studied Business Administration at the Erasmus University. After obtaining his MSc degree in June 2001, he started his career as an assistant professor at the Strategic Management department of the RSM Erasmus University. During this period he taught several undergraduate courses. In November 2002 he moved to the Financial Management department of the RSM Erasmus University, where he worked as a PhD candidate on this Thesis. Christian Huurman has published in Economische Statistische Berichten and Energy Economics (forthcoming). He currently works for an investment bank in London as an associate at Institutional Securities.

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Dealing with Electricity Prices

The 1990's witnessed the start of a worldwide deregulation process in the electricity industry. Since then, electricity prices have been based on the market rules of supply and demand. The non-storability of electricity, absence of substitutes, inelastic supply and patterns in electricity consumption, make power prices subject to mean-reversion, seasonality, frequent jumps and a complex time-varying volatility structure. Many of these characteristics cannot be observed in other commodity- or financial markets. Reforms have triggered the demand for electricity derivatives, and have led to the introduction of electronic market places where electricity can be traded on spot or forward. These markets enable market participants to allocate the price risk that they are exposed to, by selecting portfolios consisting of spot- and derivative contracts in accordance with their risk appetite. Although academic research on valuation of derivatives and portfolio theory is well-established, little is known about its applicability in electricity markets due to the aforementioned stylized facts. The scientific contribution of this research is to propose alternative methodologies for (spot- and derivative) price modelling and portfolio management in power markets. We do so by using time-series analysis, extreme value theory, panel data models and portfolio theory. Data is obtained from the most active electricity exchanges in the world. We hereby provide answers to yet unresolved issues on market efficiency, spot price dynamics, time-to-maturity effects in forward prices and structuring of the sourcing portfolio.

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