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ECONOMETRIC MODELS FOR THE ANALYSIS OF ELECTRICITY MARKETS

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Contents

List of Figures

List of Tables

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Bologna, March 2007 *Carlo Fezzi*

Chapter 1

Introduction

Since the invention of the incandescent light bulb by Thomas Edison in 1879, electricity revolutionised our way of life. Electricity is so important for social and economic development that a recent report[1] of the International Monetary Found and of the World Bank has pointed out how 1.6 billions of people do not have access to electricity and how "poor people without access to modern energy suffer from health effects of indoor air pollution; are constrained from engaging in productive activities; and suffer from poor health and education services". This "is responsible of 1.5 millions of death per year". Until recently, electricity was thought to be a typical example of natural monopoly: an indivisible, capital intensive product totally dependent upon a network structure which requires a perfect synchronization between production and instantaneous consumption. Therefore, electric industry management has historically been entrusted to state-owned, monopolistic companies.

Nevertheless, over the last decade, a wave of reconstruction interested the electric

[1]Development Commitee (2006)

industry in many countries and the liberalisation of the power sector became one of the major issues worldwide. In the early 1990s this phenomenon started in a few countries across the world (among others United Kingdom, Norway and Australia) and in the following years it gradually diffused in the European Union as well as in the United States. Ownership in the electric sector has become private rather than public, and competive markets have been introduced in many countries to boost wholesale trading. The scope was to rely on competitive forces to encourage investment and efficiency, with benefits for the overall economy.

Liberalisation also introduced new elements of risk; the major one being without a doubt electricity price volatility. Under regulation, in fact, price variation was minimal and under the strict control of public-owned commissions, which determined tariffs on the basis of average production costs. In this controlled environment the attention was focused on demand forecasting. In particular, the most sophisticated statistical techniques have been proposed to achieve satisfactory short-run predictions. On the other hand, under deregulation, price formation was delegated to the law of supply and demand. Because of the distinct characteristics of electricity, in liberalised markets price volatility has increased far beyond those of any other commodity or financial asset. Therefore, great interest has been placed on developing accurate price forecasting models. Nevertheless, the results achieved in demand forecasting are still far to be accomplished for price. The main reasons are the peculiar dynamics of electricity price, characterised by a huge volatility and by the presence of sudden, unexpected changes. The contributions in this area have mainly focused on identifying the stochastic properties of electricity prices and on proposing models to describe the time-series behaviour of price conditional mean and variance. Still at the earliest steps in this area is the study of models which are statistically accurate and also grounded in economic theory. This thesis is one of the first attempts in trying to fill this significant research gap.

The contribution of the thesis is twofold. First, it illustrates the main results achieved in the last decade in the statistical analysis of electricity markets outcomes, with special attention to the aspects which are still debated among academics and practitioners. Therefore, it proposes a novel econometric approach which ensures clear-cut inference on the price and quantity formation process in wholesale electricity markets. This model is structural, in the sense that each parameter has a clear economic interpretation, and can provide important insights on many of the unresolved aspects illustrated previously. This work has benefited from an extensive collaboration with the Energy Markets Group, and in particular with Professor Derek Bunn, started during a visiting period at London Business School.

This thesis is organised as follows. In *chapter 2,* the stylised facts concerning the electricity market liberalisation process are illustrated. The structure of wholesale markets is introduced, drawing examples from the arrangements actually existing in many countries across the world. The outcomes (price and quantity) of those markets are then analysed in the following sections.

In *chapter 3,* the statistical methods proposed to model electricity quantity and price are presented. The main focus is on high-frequency, time-series models, since in this context the most advanced methodologies are required and, therefore, have been developed. Quantity dynamics have been subject to extensive research since many decades before deregulation, whereas models to describe and forecast price are a new and expanding area of research. As showed in this chapter, some characteristics of electricity price dynamics are still unresolved. For instance, it is still debated if those time series should be considered stationary or with unit root for modelling purposes.

Since the aim of the thesis is to develop models with clear economic interpretation, in *chapter 4* the micro-economic issues that characterise wholesale electricity markets behaviour are illustrated. An important potential pitfall of deregulation is the presence of market power from the generators side and a huge amount of research has been dedicated to its study. Nevertheless, there is still a great uncertainty regarding a parameter which is crucial for those analyses: the elasticity of demand. Therefore, this "demand elasticity dilemma" is introduced.

In *chapter 5* a dynamic, structural econometric model is proposed to analyse simultaneously quantity and price in hourly wholesale electricity markets. The methodology is novel since it is grounded in economic theory and provides valid empirical inference regarding the parameters of the electricity supply and demand functions, distinguishing between short and long run. This analysis provides new insights on a well-established but unresolved aspect concerning the extent of demand elasticity to price. *Chapter 6* concludes.

Chapter 2

The electricity sector and the reconstruction process

Over the last decade, the liberalisation process in the electricity sector has spread worldwide. In the early 1990s the phenomenon started in a few countries across the world (among the others United Kingdom, Norway and Australia) and in the following years it gradually diffused in the European Union (for instance in Spain, Germany and Italy) as well as in the USA. This wide diffusion was founded upon the belief in the ability of competitive forces to deliver innovation and efficiency gains for the whole economy (Bunn 2003, Popova 2004). Competition transformed completely the structure of the market, with strong reflections in the dynamics of price. Before deregulation they were fixed by public commissions and their change over time was minimal, related to long-run pruduction costs considerations. Electricity price in liberalised markets, on the contrary, shows a tremendous volatility, higher than any other commodity or financial asset, and other peculiar features (on this point see section 3.2). As showed in the next chapters, these characteristics require the design of specifically dedicated modelling techniques. Since the scope of this thesis is to develop structural econometric models (i.e., as defined by the Cowles Commission, models where parameters have clear, direct, economic interpretation[1]) for the analysis of the newly developed electric sector, it is necessary to initially present briefly the electric industry (*section 2.1*), the restructuring process and its potential pitfalls (*section 2.2*) and the structure of wholesale electricity markets, drawing examples from the actual state of the market in some countries (*section 2.3*).

2.1 The electricity sector

Electricity is a fundamental input for the production process in any industrialised country. "Price raises, which are tolerated in other sectors, quickly become regional and national issues of concern. Similarly, any prospects of power shortages become major social and economic threat" (Bunn, 2003). For this reasons, not surprisingly, until very recent times the management of the all the electric sector (tariff designs, investment decisions and so on) was regulated by public commissions and tariffs were kept fixed over long periods of time. In this traditional structure, electricity firms were vertically integrated across the five major components (or functions) of electricity production: generation, transmission, distribution, retail and system operator.

Generation can take place through a variety of technologies, from steam power stations (using, for instance coal or natural gas) to hydroelectric ones, from nuclear to

[1]See, for example, Johnston 1984, chapter 11.

solar and wind. Each technology has different marginal and fixed costs, and no one clearly dominates the others (the only exception is probably hydropower as showed in Knittel, 2003). For this reason, in every market in the world a wide diversity of plants are operating at the same time (see also the technical analysis in section 4.1).

The *transmission* network transfers electricity over long distances, using the alternating current (AC) system invented by Tesla at the end of the XIX century. In this system, transformers are used to step up, or increase, the voltage that leaves the power plant. This enables electricity to travel over long-distance wires. When electricity reaches its destination, another transformer would then step down, or decrease, the voltage so that power could be used in homes and factories. This last phase is called *distribution* function. All the firms entitled to provide electricity to households and other small consumers form the *retail* function. The crucial feature of electricity is the impossibility of storing it in an economically feasible way. Therefore, production and consumption must be perfectly synchronised, in order to not compromise the structure of the electric grid. Furthermore, end-users treat electricity as a service at their convenience. The task of the *system operator*, therefore, is to continuously monitor the system and to call on those generators which have the technical and economical capability to respond quickly to the fluctuations of demand.

Until 15 years ago those functions were all regulated and subjected to the control of the central government. In the last decade, the ownership in the electricity sector started to become private rather then public, and the industry has been split up into the different functions. As showed in the next section, the liberalisation process presents common features in all nations, but also distinct aspects that characterise each country.

2.2 The liberalisation process

Transition from state-owned monopolies to competitive markets has not always been smooth, and skepticism and concerns have been raised in many countries. The California market collapse is probably the most exposed case (see Borenstein et al. 2002, Wolak 2003, and section 2.3.2), but also "blackouts in North America, Italy and Scandinavia have been used to argue that the electricity market liberalisation is a failed concept" (Stridbaek, 2006). Nevertheless, there are also many successful experiences, such as UK, Australia, NordPool and the PJM market (International Energy Agency, 2005).

As illustrated in the previous chapter, the electricity industry can be divided into five functions: generation, retail, system operations, transmission and distribution. Even under deregulation, the last three functions have remained monopolies, because, for their structure, no one could provide competing services in those sectors (Hunt, 2002). Furthermore these are "essential facilities" and all competitors in the other functions need nondiscriminatory access to them. For instance, one independent system operator is required to ensure the reliability of the electric system, and to continuously keep in balance demand and supply. Transmission and distribution networks are considered to be natural monopolies and access to them must be granted in order to ensure that generators have a way to reach their consumers. Nevertheless, it is important to provide incentives to the construction of new connections and transmission lines. In particular, in the European Union the long term aim is to constitute "a competitive single EU electricity market" (European Commission, 2005).

The main issues in the deregulation process can be identified as:

- eliminate as far as possible any conflict of interest between the competitive entities (retailers and generators) and the providers of the essential facilities (distribution, transmission, system operator), escluding any opportunity to discriminate;
- ensure that the market prices are settled in a truly competitive environment (see also chapter 4.2 on market power in wholesale markets);
- maintain the reliability of the system, i.e. grant short-term stability, adequate investment in both production plants and in transmission units;

Considering those points, Hunt (2002) identifies four models that represent the industry sector, each one in turn more deregulated than the previous one. Each one of these model is operating somewhere in the world. The first model is a *vertically integrated monopoly.* There is no competition, and all the function are bundled together and regulated. This model served the industry well for 100 years, and is still adopted in many countries across the world.

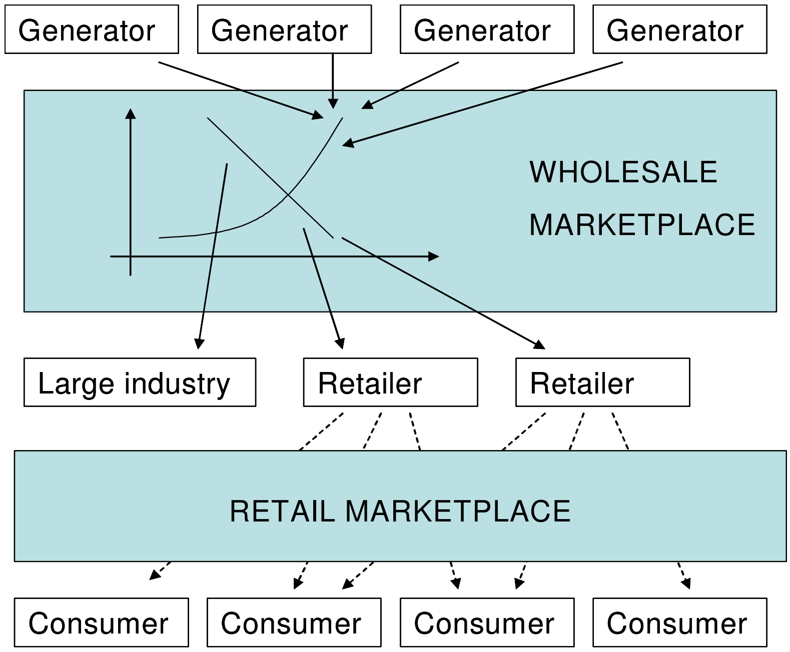
The first step towards liberalisation, adopted in the United States in the late 70s and now widely adopted in many Asian countries, is the *single buyer* model. In this framework the vertically integrated monopolist is allowed to buy electricity from many small competing independent power producers (IPP). The price at which IPPs sell is not settled by a short-term market, but rather regulated through a sort of auction, in which the utility signs long-term life-of-plant contracts with the regulator. Compared to a fully liberalised market, this situation limits the effectivness of competition, which often achieves efficiency by finding new technologies, fuels and locations.

The third model is *wholesale competition.* In a wholesale market, distribution companies and large industrial consumers buy electricity from a fully competitive generating sector. The retail function is still a monopoly. This is the structure of the US gas industry, and also the first step in the UK restructuring in 1999 and the first phase of the Italian one, in the period 2004-2007. In wholesale markets the level of electricity price is delegated to the law of demand and supply. The peculiar aspects of this commodity (among others the istantaneous nature of the product and the low demand elasticity) reflect in the dynamics of price which, as showed in chapter 3, present distinctive features and requires modelling techniques specifically dedicated. As illustrated in the next section (see also section 4.2) if the wholesale market is not truly competitive the overall economy of the system can face severe losses. The main problem with this model is how the distribution companies provide power to small consumer, over which they have a full monopoly. The retailers, in fact, could fully pass-through the cost of electricity to their clients or sell to them at a fixed price, but their choices must be closely checked since they have complete market power over their clients.

This issue is resolved, at least in theory, with the last model: *wholesale and retail competition*, represented in figure 2.1. This framework is now in place in most countries across the world: United States (PJM), United Kingdom, New Zeland, Australia, Nordic countries and Spain. A retail market pulls the benefits of having a competitive market down to the very small consumers. The big drawback of this system are its settlement costs: small consumers need to be educated and a metering and billing system need to be installed in every house.

Moving from one model to another needs a good amount of structural change

Figure 2.1: Wholesale and retail competition model



and rearrangement in the electric industry. Existing monopolistic companies must be split to ensure competition. Some institutions need to be unbundled because of the potential conflicts of interest, in particular transmission and system operation with generation (model 3) and retail with distribution (model 4). Finally, given the importance of electricity for the whole economy, one of the crucial issues is to ensure that the wholesale market is truly competitive (see section 4.2). For this reason the generation function is often required to divest during the first stages of reconstruction.

2.3 Wholesale electricity markets

The liberalisation process (see model 3 and model 4 in the previous section) has created the need for organised markets in which electricity can be traded between generators, industrial consumers and retailers. Those markets have been called power exchanges, or simply wholesale electricity markets. Participation to the exchange can be mandatory or voluntary; in the last case electricity trading is allowed also through bilateral contracts (as in Italy).

Wholesale markets are organised as auctions, in which generators submit their offers based on the prices at which they are willing to run their plants, and retailer and industrial consumers present their demand bids[2] regarding the price at which they are willing to purchase electricity (which, in turn, is determined by the forecasted demand of electricity by the small consumers, see section 3.1). Those bids are aggregated by an independent system operator in order to construct the aggregated electricity supply and demand curves, which determine the market clearing price and quantity. In chapter 3 the dynamics of those two variables are analysed using specifically dedicated time series models.

In general, in wholesale markets electricity is traded on hourly basis the day before the delivery, since the transmission system operator needs advanced notice to verify that the schedule is feasible and lies within the transmission constraints. In most markets (Italy, Spain, PJM and many others) electricity for the subsequent day is traded in 24 contemporaneous hourly auctions. As showed in the next section, this framework has inspired modelling techniques based on considering each hour of the day as a separate time series. Nevertheless, in some markets electricity is traded closer to the delivery and each period at a time. This is the case of UK where electricity is traded by half-hours and of the Ontario wholesale market, in which electricity price is settled every five-minutes through an auction.

[2]In the first phase of wholesale market operation, the demand side has often been kept regulated and an Unique Buyer has kept the responsability of purchasing power in the market for the consumer sector. This structure have been operating, for instance, in Italy, until the end of 2005.

Thereafter a few examples of market structures are briefly illustrated. These examples will provide an idea of the main issues that the design of liberalised markets has raised in many countries across the world.

2.3.1 The UK market evolution

The England and Wales (from April 2005 extended to include Scotland) electricity market began operating in 1990 and it is the oldest one in Europe. Therefore, not surprisingly, it was subject of extensive research (among others Green and Newbery 1992, Green 1996, Wolak and Patrick 1997, Wolfram 1999, Bunn 2003, Karakatsani and Bunn 2005a, 2005b). During its 15 years history it experimented a series of reforms[3], which transformed the compulsory day-ahead auction market in a bilateral trading system with a power exchange (UKPX) in which only the marginal load (around 1.5% of the total, source Weron 2006) is traded, on half-hourly basis.

The UK system is an interesting example of market evolution. The initial allocation of the British electricity market split the state owned monopoly into three companies, with only two of them, National Power (50% of share) and Powergen (30%) able to set the price (the third company was providing baseload, nuclear power, which, as showed in section 4.2, is essentially price-taking). After two years of low electricity prices, the average price began to rise slowly, inducing the regulatory body to impose an average price cap of 24£/MWh in the years 1994-96. "The price indeed averaged exactly at 24£/MWh over these two years, [. . .] hardly reflecting competitive market forces in action" (Bunn, 2003). Nevertheless, generators divestment happened during the following years, and indeed the

[3] The most significant in March 2001, called New Electricity Trading Arrangements (NETA).

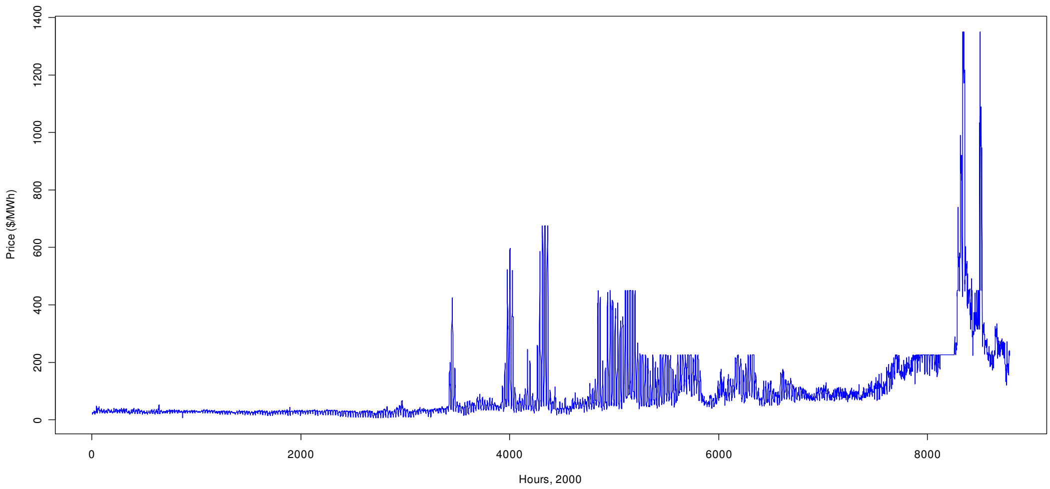
wholesale price fell. In 1999, with the introduction of NETA and the liberalisation of the retail sector, electric utilities had become vertical integrated companies, with balanced market share both in generation and retail. Therefore, despite a decline in wholesale prices, electric companies were not worse off because most of the value had migrated into the retail business.

Nowadays the UK market is one of the most competitive, and it shows a strong linkage between price and market fundamentals (Karakatsani and Bunn 2005a, 2005b). In particular, during the winter peak period, the relationship between electricity and fuel prices is rather strong (see, for instance, plot 3.8 in the next section).

2.3.2 The California Crisis

The crisis that involved the Californian electric sector in 2001 is probably the most cited example of failure of a liberalised electricity market. California was one of the first US states to launch a liberalised power market, which started in 1998. It was organised as a day-ahead auction on hourly basis. The design was similar to model 3, in the sense that the retail revenues were fixed at regulated rates. The flawless of this system showed up in 2000-01, when electricity prices begun to rise above historical peak levels, as showed in figure 2.2. Some utilities began to lose a lot of money, since they were buying at the spot price (around 120 $/MWh) and selling at fixed rates (60 $/MWh). Many concurrent causes made wholesale price to rise, among others (1) an increase in gas prices, (2) an increase of the (inelastic) demand, (3) rising prices of NOx emission credits, (4) market power problems (Borenstein et al. 2002, Wolak 2003) (5) absence of long-term contracts or vertical arrangements (Bushnell et al., 2004).

Figure 2.2: California power exchange hourly prices, from 01/01/2000 to 31/12/2000



Prices in California increased by 500% during the second half of 2000, and in the first months of 2001 they averaged over 300 \$/MWh, ten times the level of 1999. Electricity supply emergencies were in effect in winter 2000-2001, when some consumers were required to cut involuntary their demand and the system experienced several days of rolling blackouts. Californian two largest utilities became insolvent in January 2001 and stopped paying their bills for power. In April 2001 one of them declared bankruptcy. The wholesale market stopped operating in January 2001, the first bankruptcy of a power exchange in history.

2.3.3 The PJM market

In 1999, one year after the liberalisation of the California market, another power exchange started to operate in USA: the PJM, covering Pennsylvania, New Jersey and Maryland. It experienced continuous growth and is nowadays the word largest competitive market. According to Bushnell et al. (2004), it "has been widely viewed as the biggest success amongst US markets". In the PJM market electricity is bought and sold in two different markets: (1) a day-ahead one, in which most of the quantity is traded, and a (2) real time, balancing market which operates at the margin.

PJM consists of approximately 76000 MWh of capacity, including coal, oil, natural gas, nuclear and hydroelectric. Given its large dimensions, it is divided into different zones. This means that, when bottlenecks are present in the transmission system, the market splits into two or more sub-markets, with distinct supply and demand functions. In such cases, the price in the separated markets may be different. PJM market outcomes will be the subject of the empirical analysis in section 5.1 and 5.5.

2.3.4 The NordPool

The electricity reform in the Nordic European countries started in 1992, with the Norwegian Energy Act, which opened the way for the subsequent deregulation. In the following years Sweden (1996), Finland (1998) and Denmark (2000) joined the market, called NordPool, in which is traded about 40% of the quantity consumed in those four countries. There are nowadays over 400 participants in the market, including generators, retailers, traders, industrial consumers and financial institutions. Furthermore, the Pool administers an established market of power derivatives.

The NordPool is a market with unique characteristics, because of its high percentage of hydropower (55% in total, but almost 100% in Norway). This feature originates peculiar price dynamics, which have been subject of ad-hoc analyses in the recent years (see Hjalmarsson 2002, Johnsen et al. 2004, Haldrup and Nielsen 2006a, 2006b). In particular, price is very sensitive to the atmospheric conditions and, even though in general is lower than in the rest of the European countries, it may rise accordingly to unexpected water shortages. A well known case it is the "drought in 2002/03, which put the Nordic electricity market under tremendous pressure" (Stridbaek, 2006), with subsequent increase in price. The market responded in several ways: exploiting all existing Nordic power plants, increasing imports and also through demand reduction. Interesting the retail contract system influenced the reactions of small consumers to the increased price. In Sweden, one / two years contracts were the standard for residential consumers, thus there was no pass-through of high-prices into more expensive electricity bills. Therefore, no demand reduction was observable in the residential sector. Norwegian households, on the contrary, had short-term contracts linked to the spot price, which stimulated a cut in consumes. Nevertheless, the market recovered from the crisis and now it is widely seen as one of the most successful cases of liberalisation in the world.

2.3.5 The Italian power exchange

The Italian electricity market is one of the youngest in Europe and in this country the electric industry is still experiencing major changes. In particular, in 2007-08 it is expected the liberalisation of the retail market. The Italian power exchange (Ipex) started operating at the beginning of 2004 and, almost immediately, registered the highest average prices in Europe. The main reason is the shortage of generating capacity that historically affects the peninsula, which has to import 15% of its electricity consumes from France, Switzerland, Austria and Slovenia. Furthermore, the recent increase in the price of natural gas heavily affected the highly gas-dependent Italian electric sector.

The Ipex is divided into three markets: (1) a day-ahead market (MGP), in which is traded most of the quantity in 24 concurrent auctions, (2) the adjustment market (MA), which takes place immediately after the MGP closes and where utilities can adjust their schedules selling and buying electricity, and (3) a balancing market (MSD). As showed in detail the next section, electricity price is often characterised by a huge volatility. Interestingly, the presence of two day-ahead markets (MGP and MA) pushes most of the variability in the market closest to the delivery (MA), leaving the market where most of the quantity is traded (MGP) relatively calm compared to the other European power exchanges.

The Italian electricity market is facing major challenges in the next years, among others (1) investing in cross-border transmission lines, to facilitate import from other countries, (2) investing in new generation capacity, (3) encourage divestment of the incumbent ENEL to reduce its potential market power (CESI, 2005).

Chapter 3

Time series analysis of electricity market outcomes

As illustrated in the previous chapter, the original monopoly structure which has characterised the electricity sector for more than a century has been replaced in many countries by deregulated, competitive markets. Furthermore, to facilitate trading in these new markets, power exchanges have been organised. In these structures electricity is bought and sold like any other commodity, in both spot and derivative contracts. For this reason, electric utilities, power producers and marketers are now facing two fundamental sources of variability and, hence, of risk: quantity and price. As showed in this chapter, their time series present peculiar characteristics which differ from those of other commodities or financial assets and, therefore, require modelling strategies specifically dedicated.

Quantity (load) modelling and forecasting was foundamental for the electricity market management also during regulation. In the short term it was important for ensuring the reliability and security of supply and in the long term for planning and investing in new generation capacity. Electricity quantity peculiar features and the related short term forecasting methods are presented in *section 3.1.*

Before liberalisation, electricity price was regulated by appropriate public commission and its variability was minimal and associated with long term fuels cost variations. With deregulation, price volatility has skyrocketed, and a 30% average change on daily basis is common in most markets (Huisman, 2003). For this reason price modelling and forecasting has become an essential input for energy companies decision making and strategic development in the last decade. Electricity price time series present distinctive features, which are illustrated in *section 3.2*. Particular emphasis is placed on the stationarity issue (section 3.2.4) and on the modelling techniques proposed in literature (section 3.2.5).

3.1 Quantity dynamics

Developing models able to describe and forecast the dynamics of electricity quantity (which it is often indicated with the term "load" in technical papers) has been pursued since many years before the deregulation process began. Early reviews are the work of Moghram and Rahman (1989) and the collection of papers in Bunn and Farmer (1985). Short term load forecasting (in general on hourly or half-hourly basis for a daily or weekly horizon) is the task in which the most advanced techniques have been developed and implemented. For this reason, and for congruency with the general scope of this thesis, in this section I will focus only on short-term forecasting methods. For a review of long and medium term approaches see, among others, Gellings (1996).

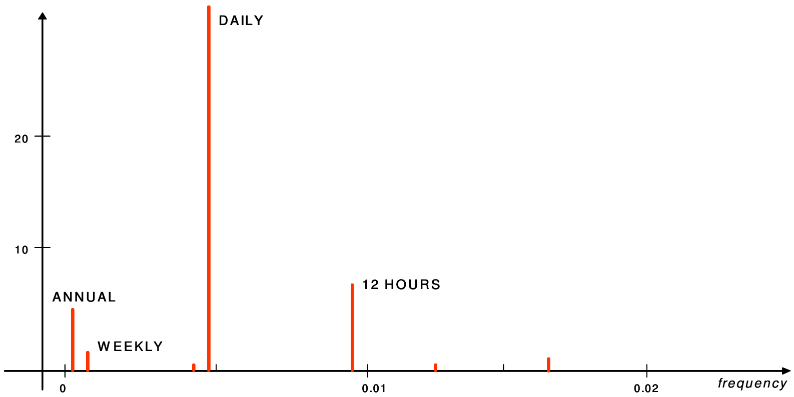
Accurate short-term forecasts are fundamental for a sensible operation of the electric system, contributing to an economical efficient and secure electric supply. In Bunn and Farmer (1985) has been estimated that a 1% increase in the forecasting error would cause an increase of 10 M pounds in operating costs per year in the UK. In fact, short-term planning of electricity load allows the determination of which devices shall operate and which shall not in a given period, in order to achieve the requested production at the fewest cost and to help scheduling generators maintenance routines. In a liberalised market, accurate load forecasts also lead to stipulate better contracts (Weron, 2006).

In section 3.1.1 the distinctive features of electricity load dynamics are presented, with emphasis on the multi-level seasonality and the strong relation with the atmospheric conditions, particularly temperature. In section 3.1.2 the most recognised short-term modelling and forecasting techniques are illustrated, including time series models, linear regressions and artificial neural networks.

3.1.1 Determinants of quantity dynamics

The strong seasonal component is probably the most evident feature of electricity load dynamics. Cycles with annual, weekly and daily periodicity characterise every power sector across the world. The daily cycle encompasses the highest part of variability (see the periodogram in figure 3.1) and follows the working habits of the population. As showed in figure 3.2, this cycle can be different from market to market, and may present one (California) or two (Spain) peaks per day, according to the atmospheric conditions and the living habits of the population. Night hours present a low demand, which starts increasing roughly around 6.00-7.00 a.m., when population awakes and the workday begins. In figure

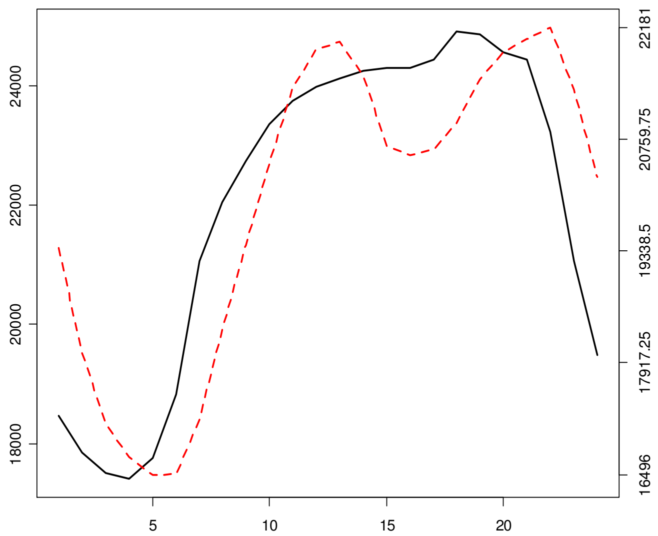
Figure 3.1: Periodogram of UK electricity half-hourly load data (1st of january 2004 - 23rd of january 2006)



3.2, Californian load reaches his peak around 17 p.m., and then decreases gradually until 1 a.m. On the other hand, Spanish load presents two peaks per day, at 13 a.m. and at 10 p.m. In any case, however, a strong daily cycle is always a fundamental feature of the electricity load patters. For this reason in wholesale electricity markets electricity is traded on hourly basis (see section 2.3). Has been even argued that electricity traded in different hours should be treated as different commodities for modelling purposes (Guthrie and Videbeck, 2002). As showed in the next section, the approach of developing a separate model for each hour of the day, introduced in Ramanathan et al. (1997), has became rather established in forecasting demand.

In general, the weekly cycle encompasses a small portion of variance, and it is originated by the working cycle of the population as well. Sunday and Saturday load profiles, in fact, are systematically lower than weekdays ones. This feature causes also a particular steep increasing of electricity generation in the early hours of Monday, and a steep decreasing in the late Friday. This variation often reflects in prices, which are

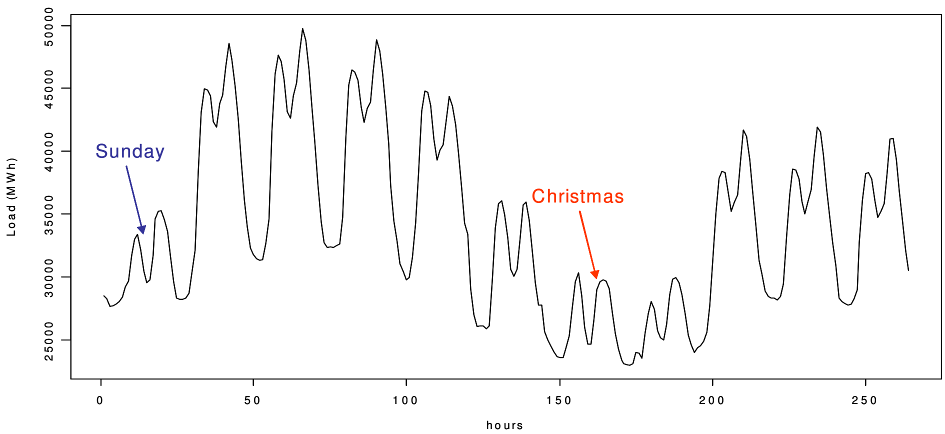
Figure 3.2: Hourly average load in California in MWh (straigh line, 01/01/1999 - 31/12/1999) and Spain (dotted line, 01/01/1998 - 31/12/2003)



particularly unstable in those two weekdays. A ‘weekend effect’ takes also place during national holidays, when working activities are partially suspended and, hence, electricity consumption is lower. During those days electricity load forecasting is particularly difficult, and it is often based on the personal experience of the operators more than on sophisticated statistical modelling. See, for instance, the peculiar patters of the Italian electricity load during the Christmas holidays 2004 plotted in figure 3.3.

The third seasonal factor, the annual cycle, is connected with the smooth variation of temperature through the whole year. Electricity, in fact, can be used for both heating and air-conditioning purposes creating in many markets two peaking seasons (winter and summer) and two low demand seasons (spring and fall). This behaviour is evident in the Spanish demand time series presented in figure 3.4. In Italy the heating system is mainly

Figure 3.3: Hourly loads in Italy, from 19/12/2004 to 29/12/2004.



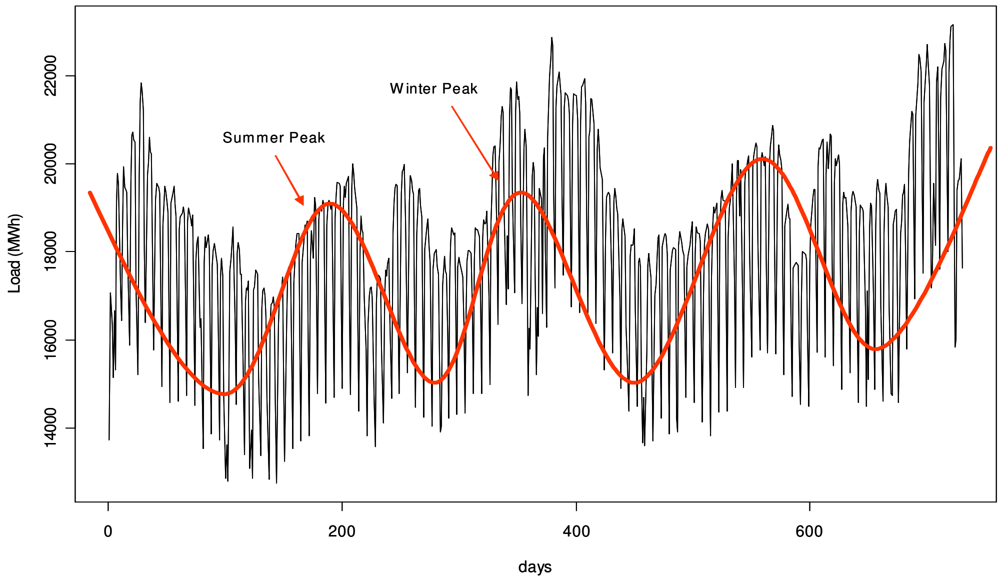
gas based and demand reaches its peak during the summer. In general, however, electricity load and atmospheric temperature are characterised by a strong non-linear relationships, which has been illustrated, among others, in Engle et al. (1986) and Henley and Peirson (1997). Atmospheric conditions not only originate the yearly cycle, but also explain short-term changes in electricity consumption. As showed in the next section, these are the most important exogenous variables when developing short-term load forecasting models.

3.1.2 Short term forecasting models

Short-term load forecasting has been widely studied in literature. Since the 70s, many techniques have been proposed and compared without the establishment of a clear winner. However, those studies enhanced sensibly quantity forecasting, achieving a predictions error of 1-2% on hourly basis (Bunn, 2000). Among the most recognised methods one may cite:

i. Exponential smoothing

Figure 3.4: Daily average load in Spain, 1 January 1998 - December 1999, seasonal cycle superimposed



ii. Dynamic regression models

iii. Time series methods

iv. Artificial neural networks

Exponential smoothing is probably the plainest stochastic model for a generic time series, but has proven quite appealing in quantity forecasting (for a recent comparison see Taylor et al., 2006). It is a pragmatic approach to forecasting, whereby the prediction is constructed as an exponentially weighted average of the past observations. Indicating with q_t the electricity traded quantity, the smoothing algorithm can be written as:

$$l_{t|t-1} = \alpha q_{t-1} + (1 - \alpha) l_{t-1|t-2} \ ,$$

where $l_{t|t-1}$ is the smoothed series at time t calculated using the information available at time t-1. Applying recursively the algorithm, each prediction (i.e. each smoothed value) is obtained as the weighted average of the current observation and the previous smoothed value. In addition to simple exponential smoothing, more advanced models based on the same priciple have been developed, in order to accommodate series with seasonality and trend. Among others, the Holt-Winter's method (see, for a discussion, Bowerman and O'Connell, 1979), which has been implemented in Taylor (2003) and Taylor et al. (2006), divides the series into three component:

$$
\begin{aligned}
l_t &= \alpha(q_t - S_{t-s}) + (1-\alpha)(l_{t-1} + T_{t-1}) \ , \\
T_t &= \beta(l_t - l_{t-1}) + (1-\beta)T_{t-1} \ , \\
S_t &= \gamma(q_t - l_t) + (1-\gamma)S_{t-s} \ ,
\end{aligned}
$$

where T_t is the trend, S_t the seasonality and the prediction can be obtained as an additive or multiplicative interaction of the three components T_t, S_t and l_t.

The *dynamic regression* modelling approach assumes that the quantity traded on the market can be decomposed in a base level (the intercept) and a component which is linearly dependent to a set of explanatory (exogenous) variables, like atmospheric conditions (such as temperature and air humidity) or the past values of quantity. Indicating with z_t the explanatory variables, the model can be written as:

$$q_t = b_0 + b_1 z_{t1} + b_2 z_{t2} + ... + b_3 z_{t3} + u_t \ , \tag{3.1}$$

with u_t residual component, with mean zero and assumed, in general, Gaussian white noise. Forecasts based on more than one equation (3.1) can also be developed as, for instance, it has been done in Papalexopulos and Hesterberg (1990). Their model produces an initial peak demand forecast based on a set of explanatory variables such as forecasted temperature, day of the week and lagged temperature and load. This estimate is then modified using the hourly forecast obtained with another regression through an exponential smoothing procedure. Hyde and Hodnett (1997) proposed an adaptable regression model for day-ahead forecast, which identifies weather-insensitive and sensitive demand components. Linear regression on historical load and weather data is used to estimate the parameters of the two components. Others relevant contributions in this area are, for instance, Ružić et al. (2003) and Ramanathan et al. (1997).

Time series processes are probably one of the most established modelling techniques for electricity demand, when the focus is on the forecasting performances. A review of this methodology is beyond the scope of this thesis; for an extensive illustration of time series analysis I suggest to refer to the wide literature available (among others Box and Jenkins 1970, Hamilton 1994, Dagum 2002). The most popular stochastic processes applied to electricity demand modelling are the ARIMA and the transfer function models. The generic ARIMA process, indicating with B the backshift operator, can be written as:

$$\phi(B)\nabla^d q_t = \theta(B)u_t \ ,$$

where:

$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - ... - \phi_p B^p$ is the autoregressive component (AR);

$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - ... - \theta_q B^q$ is the moving average component (MA);

$\nabla q_t = q_t - q_{t-1} = (1 - B)q_t$ is the differencing operator (I) to achive stationarity[1];

u_t is the residual component assumed to be white noise and Gaussian.

The parameters $\phi(B)$ and $\theta(B)$ can be estimated through Maximum Likelihood. The process can be augmented including also a seasonal component (SARIMA). In this technique (as in the exponential smoothing) the only information used to forecast electricity demand is the one embedded in the historical values of the series itself.

The classical ARIMA approach has been applied to electricity load forecasting also introducing a few changes. For instance, Nowicka-Zagrajek and Weron (2002) include an hyperbolic specification for the error component, which provides a better fit in the data they analysed. A non-Gaussian ARIMA model for short-term load forecasting is proposed also in Huang and Shin (2003). Furthermore, Huang (1997) implements a threshold autoregressive model, a class of processes introduced by Tong (1983). The underlying idea is to fit a non-linear process identifying some thresholds in which the process can be effectively approximated with linear functions.

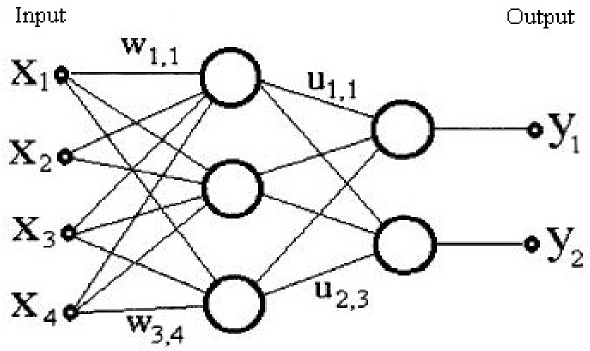
Using the transfer function method one can also incorporate exogenous or deterministic variables in the model. For instance, atmospheric temperature (*temp*) can be included as explanatory variable obtaining:

$$q_t = \frac{\omega(B)}{\sigma(B)} temp_{t-s} + n_t \ , \tag{3.2}$$

with:

[1] For a primer on stationarity see section 3.2.2.

Figure 3.5: Structure of a MLP neural network: input variables (Xs), neurons (circles), output variables (Y) and weights (w and u).



$\omega(B) = \omega_0 - \omega_1 B - \omega_2 B^2 - ... - \omega_r B^r$;

$\sigma(B) = 1 - \sigma_1 B - \sigma_2 B^2 - ...\sigma_s B^s$;

n_t : stationary process with zero mean, indipendent from *temp*, in general white noise but eventually described by an ARIMA process.

This approach has been implemented, among others, in Cho et al. (1995) and Moghram and Rahman (1985).

Artificial neural networks started to be implemented for electricity demand forecasting in the early '90s, and they rapidly gain a widespread popularity both among academics and practitioners. This method is inspired to the neural system of the living things. Every network is formed by a group of elements, called neurons. Every neuron receives its inputs from others neurons and generates an output that can be further elaborated (see Haykin, 1994 for an extensive illustration of this methodology). Neural networks are a data driven approach since they require that the researcher formulates only a few initial assumptions. For this reason they are particularly suited when a lot of data are available, but the relations among the variables are not clear *a priori*, as it often happens for electricity markets outcomes. Furthermore, they are able to approximate every continuous function with extreme precision (Zhang, 1998). On the other hand, they behave like “black boxes” and the results often lack of interpretability. Among the first application of neural networks to electricity load forecasting is the work by Park et al. (1991), in which a multilayer perceptron (MLP) network is used to predict peak and total daily load. In figure 3.5 is represented the structure of a MLP, probably the most established neural network type. In each neuron, called perceptron, the output is produced applying a non-linear function (called activity function) to a linear combination of the inputs:

$$ou_j = h(\sum_{i=1}^{n} w_i in_i - k) \ , \tag{3.3}$$

with:

ou_j = output signal;

in_i = input singnal, which can be initial input or other neurons output;

w = weights;

k = intercept;

$h(.)$ = activity function.

Activity functions can be any functional form, in general non linear (the most diffused are the sigmoid functions or the hyperbolic tangent). For more information one can refer to Haykin (1994). MLP are often applied by electric utilities and system operators to produce their official short-term forecasts. Examples are the model proposed in Khontazad et al. (1998), in which various systems of neural networks are combined to produce optimal predictions. Other interesting contributions are, for instance, Mohammed et al. (1995), Asar and McDonald (1994) and Czernichow et al. (1996). For a review see Hippert (2001).

In the last decade, a modelling approach which can be implemented alongside with any of those methodologies gained growing recognition and diffusion. It consists in developing a separate model for each of the hour of the day (or half-hours, if this is the trading unit of the market of interest). This technique was first introduced in Ramanathan et al. (1997) to compete in a forecasting contest organised by the Puget Sound and Light System Company (an electric utility company based in New York). This approach is inspired by the idea that each of the 24 hours presents specific demand characteristics (see section 3.1.1) which are not shared by the other hours of the same day. For instance, the hour 17 (peak) loads of the same week are likely to be much more similar among them that the hourly loads from hour 11 to 17 of the same day. Given the large amount of data which is generally available, it is often a sensible option to reduce this heterogeneity defining 24 separate hourly time series from the original one. This choice often proves quite appealing for forecasting purposes. The model proposed in Ramanathan et al. (1997), for instance, was simply a dynamic regression using past load and temperature as exogenous regressors. Nevertheless, it outperformed all the others, much more complex, approaches (for instance, the time-varying spline of Harvey and Koopman, 1993, and the neural network of Brace et al., 1993) and the own company experts predictions.

After this first contribution, many researchers followed the path indicated by Ramanathan et al. (1997), and developing separate models for each hour of the day become a rather established procedure. It has been used, for instance, with ARIMA and SARIMA models (Soares and Sousa 2003, Soares and Medeiros 2005) and neural networks (Khontazad et al. 1998). With the birth of liberalised markets, it has also gradually been adopted for forecasting electricity prices (see, for instance, section 3.2.3 or Karakatsani and Bunn, 2005a). Also the model proposed in chapter 5, even though not developed for forecasting purposes, is based on this approach.

As showed in section 2.3, in deregulated markets, price and quantity are determined simultaneously. In this framework, it is significant to analyse the extent in which electricity demand is affected by the level of price (i.e. if electricity demand is price elastic) or if price can be helpful to predict future traded quantity (i.e. if electricity quantity is price responsive). This issue is still debated (see section 4.3) and the model presented in chapter 5 can give, inter alia, important insights on this point. Nevertheless, price has already been used to improve quantity forecasts in Chen et al. (2001). On the other hand, load is extensively used to improve price forecasting models, as showed in the next sections.

3.2 Price dynamics

An evident consequence of the electricity markets liberalisation is the increase in the uncertainty of electricity prices. Spot prices present an extremely high volatility and, therefore, modelling and forecasting electricity prices in the short term assumes critical importance for trading, derivative evaluation and risk hedging. Even though forecasting electricity loads has reached a comfortable state of performance (Bunn, 2000), achieving the same results for prices seem still a long way to go. The task in fact has proven to be quite challenging to several researchers because of the peculiar characteristics of electricity prices, which differ dramatically from those of other commodities.The distinctive feature of electricity is indeed the instantaneous nature of the product. In fact, across the grid, production and consumption are perfectly synchronised, without any capability of storage. For this reason inventories cannot be used to arbitrage prices over time and, when demand is higher than supply, prices can rise more than proportionally such that high and mean-reverting spikes may occur.

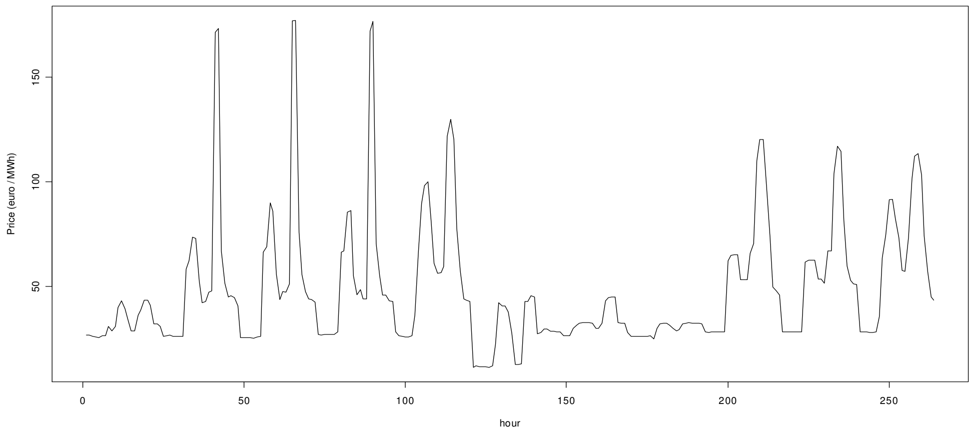
In section 3.2.1 the distinctive features of electricity price are illustrated, section 3.2.2 discuss to the stationarity issue, which is still debated for these time series, whereas section 3.2.3 reviews the modelling techniques proposed in literature.

3.2.1 Determinants of price dynamics

Not surprisingly, the most important factor affecting price is indeed the demand dynamic. Since the short term elasticity of demand is very low (see section 4.3) electricity price profiles appear to be often driven by the load ones. Therefore, electricity price dynamic inherits some of the distinctive features of demand, such as the multi-level seasonality. As showed in section 3.1.1, load is characterised by three seasonal cycles: yearly, weekly and daily. The same behaviour is evident in electricity prices time series, as showed in picture 3.6.

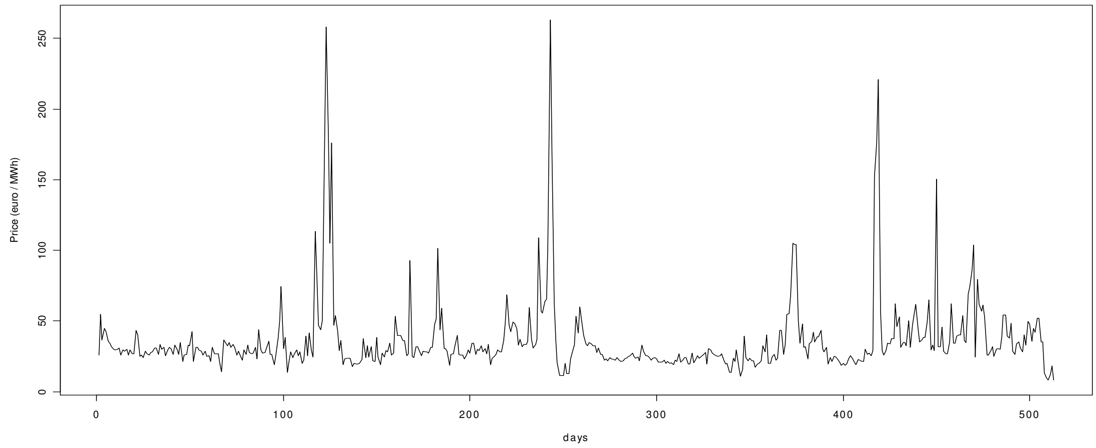
On the other hand, price time series are much more variable than load ones (see for example the coefficient of variations computed in section 5.1.1). Comparing electricity

Figure 3.6: Hourly electricity price in Italy, from 19/12/2004 to 29/12/2004.



demand (figure 3.3) and electricity price (figure 3.6) in the same days, in fact, it is clear how the latter displays a structure which is much more complicated than a simple functional rescaling of demand. A number of salient features of price dynamics have been analysed in literature; an extensive illustration can be found in Knittel and Roberts (2005). Among others, high volatility with evidence of heteroskedasticity and the presence of sudden jumps are probably the most noticeable. The first one refers to the presence of low volatility clusters followed by unstable periods (Escribano et al. 2001) and it is typical of financial assets time series. This aspect has been widely modeled using Arch and Garch processes (Engle 1982, Bollerslev 1986) in Goto and Karolyi (2004), Leon and Rubia (2004), Worthington and Higgs (2004), Knittel and Roberts (2005) and Misiorek et al. (2006), among others. The second one (spikes) is a peculiar characteristic of electricity prices, which originates from the impossibility of storing electricity in an economic feasible way. Furthermore, supply and demand must be balanced continuously to prevent the network from collapsing. Hence, since shocks cannot be smoothed through inventories, some extremely and unexpected high

Figure 3.7: APX (Netherlands) daily price, weekdays, from 01/01/2001 to 31/12/2002

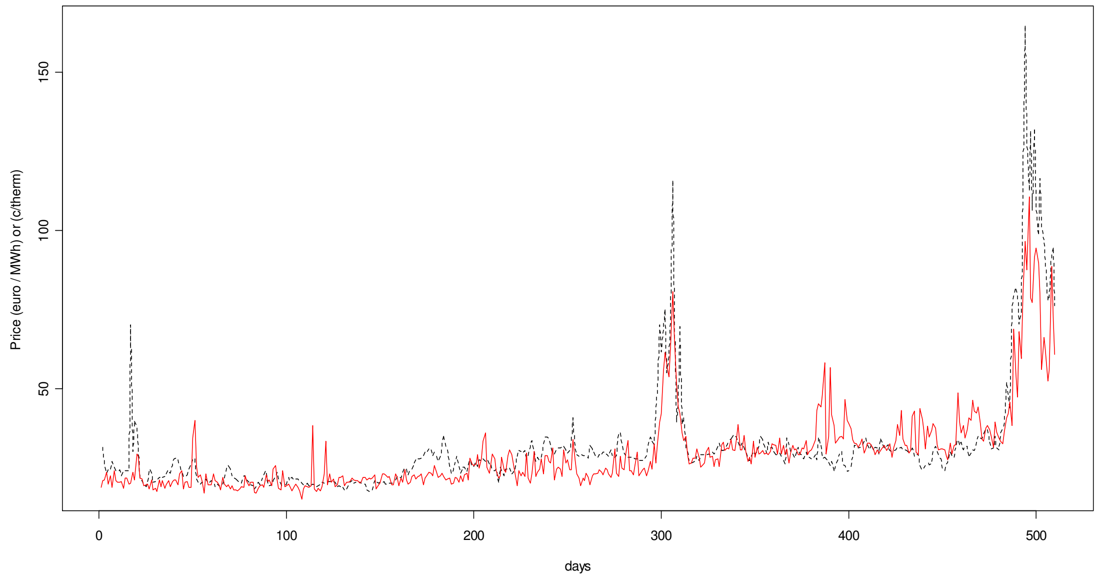


prices may occur. Those events are evident from the plot in figure 3.7.

There are a number of market structure elements, which help to explain these unusual time series characteristics (see section 4.1 for an extensive illustration). The simplest observation is that with a diversity of plants, of different technologies and fuel efficiencies on the system, at different levels of demand, different plants will be setting the market-clearing price. For this reason, an important variable for determining price is the amount of power plants available to produce in each day (i.e. the available capacity on the system which, in technical papers, is often called "margin"). As showed in detail section 4.1, if some power plant bids are missing the aggregate supply curve shifts upwards. This feature is not substantial when demand is low (i.e. in the baseload) but will affect price considerably in the peak and it is one of the reasons which may determine the above mentioned spikes.

Furthermore, since the price-setting power plant is often a fuel burning one (particularly during the peak) electricity price is particularly sensitive to fuel price movements.

Figure 3.8: Electricity (euro / MWh) and gas (c / therm) daily price in UK, from 01/01/2004 to 14/12/2005



Above all, the price emerging from the gas market, which has been liberalised in many countries and hence presents often a high volatility, is an important determinant of the electricity one (see, for instance, figure 3.8). As showed in Serletis and Shahmoradi (2006) the relation between gas and electricity price is strong, non only on the mean but also on the variace.

In the Nordic countries, where hydro is the main source of energy generation, atmospheric factors play also an important role. For instance, Hjalmarsson (2002) identifies rainfall, snowfall and snow melting as supply shifters of the electricity generation sector in the Nord Pool. In this market a severe drought can push considerably the price of electricity upwards, has it happened, for example, during the winter 2002/03 (see section 2.3.4 and Stridbaek, 2006).

From these findings, it is clear how the complex relations and dynamics which characterise electricity prices require modelling techniques specifically dedicated. On the other hand, the birth of liberalised market is a recent phenomenon (see section 2.2) and the research in this field is still at its first steps. Reaching the performance achieved in load forecasting is still a long way to go and, according to some researchers (Weron and Misiorek, 2005) may turn out to be unfeasible. In the next sections the most established modelling approaches are reviewed and illustrated. Before doing so I will present an issue which is still an open question in the analysis of electricity markets outcomes time series and which deserves a careful examination.

3.2.2 The stationarity issue

In the literature and among practitioners there is an overall agreement on the high frequency electricity prices features that have been presented in the previous section (seasonality, heteroskedasticity and the presence of sudden jumps). On the contrary, a crucial element as the stationarity of electricity prices is still an open question. When discussing time series analysis, investigating the stationarity of the data generating process is frequently a key aspect of the modelling procedure. As discussed in Dixit and Pindyck (1994) and Baker, Mayfield and Parsons (1998), for instance, modelling energy price time series as trend mean-reverting or as random walk may have very different implication for investment decision and option pricing. This issue has been extensively analysed in Pindyck (1999) using 120 years of coal, oil and gas prices, showing that non-stationary processes best describe the data. Also in the context of empirical electricity price modelling, this issue should be carefully examined, in particular if, as in the model proposed in chapter 5, is given to the estimated parameters an economic interpretation.

A stationary variable is a variable in which mean and variance do not evolve over time. More formally, indicating with y_t the price of electricity at a given hour t, this time series is defined weakly stationary if its first two moments are constant over time, and so:

$$E[y_t] = \mu \ ,$$

$$E[(y_t - \mu)^2] = \sigma^2 \ ,$$

$$E[(y_t - \mu)(y_{t-s} - \mu)] = \gamma(s) \ ,$$

where μ, σ^2 and $\gamma(s)$ are finite and independent of t[2]. One the basis of classical econometric theory is the fact that the variables involved in the analysis are stationary (Hendry and Juselius, 2000). Under this condition, classical statistical inference is valid, whilst assuming this assumption when it doesn't hold can induce serious statistical mistakes. In fact, modelling non stationary variables as they would be stationary invalidates in the most cases all the inference procedures leading to a problem known in literature as spurious regression or "nonsense correlation", with extremely high correlation often found between variables for which there is no causal explanation.

In such conditions many statistical inference tools such as the Student's t, the F test and the R^2 are no longer valid. A complete illustration of this topic is beyond the purpose of this text, for a detailed and extensive analysis I suggest to refer to the wide literature available, for example: Granger and Newbold (1974), Hendry (1980), Phillips (1986) and Hendry and Juselius (2000).

[2]A variable is defined as "strict stationary" when the entire joint distribution is constant over time.

In most paper focused on empirical electricity price modelling (see, for instance, De Vany and Walls 1999, Atkins and Chen 2002, Goto and Karolyi 2004, Haldrup and Nielsen 2004, Karakatsani and Bunn 2005a, Knittel and Roberts 2005) the issue of non stationarity is investigated through standard procedures like the augmented Dickey Fuller test and the Phillips Perron test. The first one is probably the most popular unit root test and refers to the work by Dickey and Fuller (1979), in which the null hypothesis that a series y_t contains a unit root (i.e., it is non-stationary) is tested against the alternative of stationarity through the following regression:

$$y_t = \phi y_{t-1} + u_t \ ,$$

or, the more common:

$$\Delta y_t = (\phi - 1) y_{t-1} + u_t \ , \tag{3.4}$$

with u_t residual component i.i.d. Gaussian with zero mean. The null hypothesis of non stationarity (i.e. of unit root) is thus H_0:$\phi = 1$ against the alternative H_1: $\phi < 1$. In fact, a process defined as:

$$y_t = y_{t-1} + u_t = y_0 + \sum_{j=0}^{t-1} u_{t-j}$$

does not converge to a mean value over time, nor presents constant variance since $V[y_t] = t\sigma_u^2$. This process is called random walk, or integrated of order one I(1), since it needs to be differentiated ones to achieve stationarity. Stationary processes, on the other hand, are called integrated of order zero, or I(0). The autocorrelation function of processes with a unit root is very persistent whereas in I(0) processes it decays exponentially to zero.

The hypothesis of unit root can be tested using a standard t-ratio test on the parameter ϕ. However, under non-stationarity the statistic computed does not follow the standard Student's t distribution but rather a Dickey-Fuller distribution, whose critical values has been computed using Monte Carlo techniques in Dickey and Fuller (1979). Equation (3.4) shows the simplest form of the test. This has been subsequently modified to account for an overall process mean different from zero, a trend and an autocorrelated error term. This leads to the augmented Dickey – Fuller (ADF) test (Dickey et al., 1984 and 1986):

$$\Delta y_t = \phi y_{t-1} + \sum_{i=1}^{p} \psi_i \Delta y_{t-1} + \mu + \gamma t + u_t \ ,$$

where the number p of lagged differences is chosen long enough to capture autocorrelated omitted variables that would, otherwise, enter in the error term, and, therefore, to ensure that u_t is approximately white noise. The choice of the appropriate lag-length is crucial since too few lags may result in over-rejecting the null when it is true (affecting the size of test), while too many lags may reduce the power of test (and so its ability of rejecting the null when it is false). For some guidelines and for a further discussion of this topic see, for example Banerjee et al. (1993).

An alternative approach to take into account serial correlation in the residual component is the one proposed by Phillips and Perron (1988). Rather then adding lagged differences of the dependent variable in the regression equation they propose a non-parametric correction of the test statistic which considers the effect that autocorrelated errors have on the results. This methodology is based on the intuition that in presence of autocorrelated residuals the variance of the stochastic component in the population:

$$\sigma^2 = \lim_{T\to\infty} E[T^{-1}S_T^2] \tag{3.5}$$

(with $S_T = \sum_{j=1}^{t} u_j$) differs from the variance of the residuals in the regression equation:

$$\sigma_u^2 = \lim_{T\to\infty} T^{-1}\sum_{t=1}^{T} E(u_t^2) \ . \tag{3.6}$$

Indicating with S_u^2 and $S_{T\varrho}^2$ consistent estimators of the quantities in equation (3.5) and equation (3.6) (see Phillips and Perron, 1988 and Banerjee et al., 1993 for a comprehensive discussion of the topic), the PP Z-statistic for the null hypothesis of $\phi = 1$ (for a process with mean but no trend) is defined as:

$$Z(\hat{\phi}) = T(\hat{\phi} - 1) - \frac{1}{2}(S_u^2 - S_{T\varrho}^2)\left[T^{-2}\sum_{t=2}^{T}(y_{t-1} - \bar{y}_{-1})^2\right]^{-1} \ .$$

The corresponding statistics for a process with zero mean or with mean and trend are reported in Perron (1988). The critical values are the same as for the DF test.

An alternative approach is to construct a test under the null hypothesis of stationarity as proposed by Kwiatkowski, Phillips, Schmidt, and Shin (1992) and implemented in analysis of electricity spot price in Atkins and Chen (2002) and Haldrup and Nielsen (2004). The KPSS test derivation starts with the model:

$$y_t = \beta^t D_t + \mu_t + u_t \ ,$$

$$\mu_t = \mu_{t-1} + \varepsilon_t \quad \varepsilon_t \sim i.i.d.(0, \sigma_\varepsilon^2) \ ,$$

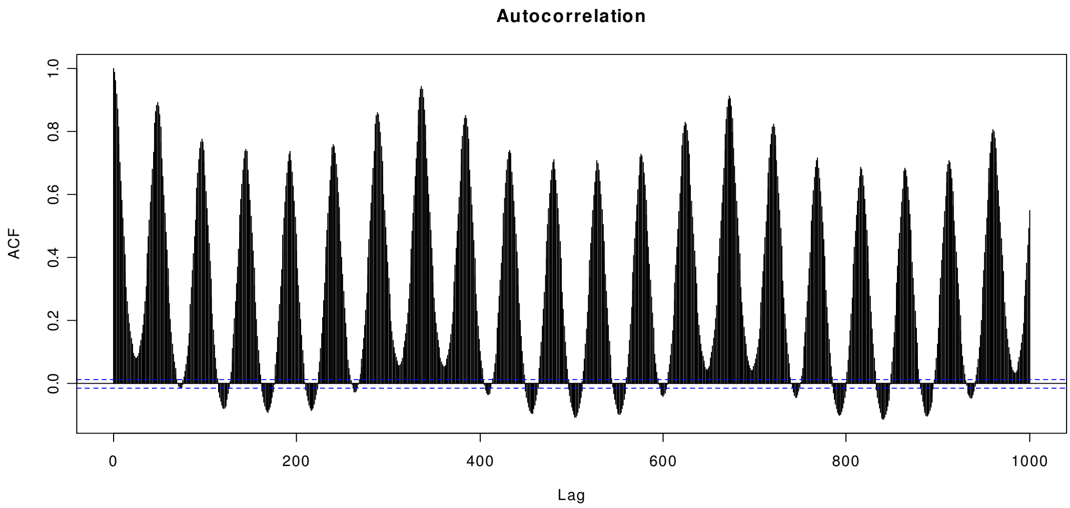
where D_t contains the deterministic components (mean, trend or seasonal dummies as showed in Jin and Phillips, 2002) and u_t is $I(0)$ and may be heteroskedastic. The null hypothesis that y_t is $I(0)$ is formulated as H_0: $\sigma_\varepsilon^2 = 0$, which implies that μ_t is a constant. The KPSS statistics is the Lagrange multiplier (LM) or score statistics for testing $\sigma_\varepsilon^2 = 0$ against the alternative $\sigma_\varepsilon^2 > 0$, and it is given by:

$$KPSS = \left(T^{-2} \sum_{t=1}^{T} S_t^2 \right) / S_{T\varrho}^2 \ ,$$

where S_t^2 and $S_{T\varrho}^2$ defined as previously. Kwiatkowski et al. (1992) showed that under the null the statistic converges to a function of a standard Brownian motion that depends on the form of the deterministic terms D_t but not on the coefficient values β. Critical values for this distribution have been calculated with simulation methods.

One must remember that results from any unit root test must be taken carefully, in particular when, as in the case of electricity price (or load) time series, the alternative is a very persistent stationary process. In fact, as showed in Campbell and Perron (1991), in finite samples “any trend-stationary process can be approximated arbitrary well by a unit root process (in the sense that the autocovariance structure will be arbitrarily close)”, and the reverse is also true. For this reason there is a trade off between size and power in unit root test (Blough, 1992), and there is an high probability of falsely not reject the null when the true data generating process is a nearly stationary process. Furthermore, in the case of electricity markets spot prices these results are even weaker, considering that the strong seasonality and the presence of sudden mean-reverting spikes affect the power and size of the standard unit root tests (Cavaliere, 2004). The autocorrelation function of electricity markets outcomes is indeed persistent, and strongly reflects the daily seasonality. As an example, figure 3.9 plots the autocorrelation function computed using UK half hourly

Figure 3.9: Autocorrelation function: UK half-hourly loads, from january 2004 to may 2006



quantity in the years 2004-2006. Autocorrelation is still very high after 1000 lags, and the daily and weekly seasonal patters are both evident in the graph. Trying to overcome these issues, Escribano et al. (2002) propose an unit root test studied to account for the presence of outliers (spikes) and heteroskedastic errors. Through this procedure they refuse the null hypothesis of unit root for some electricity price series (Argentina, Australia, New Zealand, Nordpool and Spain).

Nevertheless, the stationarity of electricity price (and quantity) time series cannot be assumed as a general rule. Stevenson (2002) for instance, identifies a unity root in the Australian market prices and decides to use the differentiated series to obtain a stationary mean. The same approach is followed by Contreras et al. (2003) and Conejo et al. (2004) for California, Spain and PJM interconnection (Pennsylvania, New Jersey and Maryland) data. Goto and Karolyi (2004) decide to treat USA, Nord Pool and Australian electricity prices as stationary, even if they stress that the tests they apply (ADF and PP) do not show robust stationarity evidence, in particular for the Nord Pool. Weron et al. (2003) analyse the stationarity issue in the latter market using the Average Wavelet Coefficient (AWC) method of Simonsen et al. (1998) finding contrasting results (i.e. they find that using data with different time frequency leads to different conclusions). Haldrup and Nielsen (2004) test stationarity via the PP and the KPSS test, refusing the null hypothesis in both cases. For this reason they argue that neither an I(1) nor an I(0) description of the Nord Pool time series is appropriate. On this basis they propose a fractionally integrated process: a process that is on the border between stationarity and non stationarity, presenting both long memory and mean reversion (for a complete illustration about long memory processes see, for example, Geweke and Porter-Hudak 1983, Beran 1994, Baille 1996). Atkins and Chen (2002) reach the same conclusion analysing a different market, and derive an ARFIMA (autoregressive fractionally integrated) model for Alberta hourly electricity prices. On the contrary, it must be noticed that in many papers (for example Karakatsani and Bunn 2005a, Knittel and Roberts 2005) non-stationarity is tested, rejected and electricity prices are treated as a stationary and mean-reverting process.

As illustrated in section 3.2.1 seasonal patterns are one of the most important determinants of electricity price dynamic behaviour. As showed in Maddala and Kim (1998), strong seasonality can influence the power and the size of the standard unit root tests. According to the different source of seasonality, it is possible to distinguish between deterministic and stochastic seasonality. The first one can be modeled inserting a deterministic component in the equation, such as seasonal dummy variables or sinusoids. This kind of seasonality is perfectly predictable and never changes in shape. The second one is generated by a stochastic process and can vary with time.

As showed in section 3.1.1, the strong seasonal variation of load and prices on the daily horison inspired the development of empirical approaches based on modelling separately each hour. This choice is able to rule out all the seasonal variation on the daily cycle, but leaves in the series the weekly one. The remaining weakly seasonal process can be written, for example, as:

$$y_t = \phi_7 y_{t-1} + u_t \ .$$

In this case if $\phi_7 < 1$ the process is stationary and its seasonal mean and variance are stable over time, otherwise, if $\phi_7 = 1$ the process is said to be seasonally integrated or to have seasonal unit root (Hylleberg at al., 1990). Such processes cannot be captured using deterministic seasonal dummies since the seasonal components can drift substantially over time. Stationarity can be achieved using the seasonal differencing operator, as advocated by Box and Jenkins (1970), and indicated by $\Delta_d = (1 - B^d)$, with d seasonal periodicity.

Rubia (2001) extends to the weekly case the HEGY seasonal unit root test (Hylleberg et al., 1990) in order to check the necessity and the validity of the application of the seasonal differencing operator in the case of electricity demand data modelling. Angel and Rubia (2004) use a similar methodology and find evidence of seasonal unit root in the Spanish electricity daily prices. The HEGY test (Hylleberg et al., 1990) is based on the factorisation of the weekly differencing polynomial $(1 - B^7)$ in $(1 - B)S(B)$, with $S(B) = (1 + B + \ldots + B^6)$. Therefore, the null hypothesis of unit root at seasonal frequency can be expressed in a unit root at zero frequency and three pairs of complex roots at the seasonal frequency $k\varpi$, with $k = 1, 2, 3$ and $\varpi = 2\pi/7$. Referring to Rubia (2001) for the technical aspects involved, the test can be derived as:

$$\Delta_7 y_t = \alpha + \beta t + \sum_{j=2}^{7} \alpha_j D_{jt} + \sum_{j=2}^{7} \gamma_j D_{jt} t + \sum_{j=2}^{7} \pi_j z_{j,t-1} + \sum_{r=1}^{p} \phi_r \Delta_7 y_{t-r} + u_t \ , \qquad (3.7)$$

where each of the regressors $z_{j,t}$ are defined on the seasonal frequencies $k\varpi$ as follows:

$$z_{1,t} = \sum_{j=1}^{7} \cos(0j) B^{j-1} y_t = S(B) y_t \ ,$$

$$z_{2k,t} = \sum_{j=1}^{7} \cos(kj\varpi) B^{j-1} y_t \ ,$$

$$z_{2k+1,t} = -\sum_{j=1}^{7} \sin(kj\varpi) B^{j-1} y_t \ .$$

This specification is the most general, and includes a drift (μ), a linear time trend (β), deterministic seasonal dummies (D_{jt}) or seasonal drifts (γ_t) and it is estimated through Ordinary Least Squares (OLS). As in the ADF test (Dickey and Fuller 1979, Dickey et al., 1986) a number of lags p of the dependent variable are included in order to achieve zero autocorrelation.

Compared to other techniques (see for example Dickey et al., 1984) the HEGY approach has the remarkable feature that one can test for unit roots at some frequencies without assuming that there are unit roots at some or all of the other frequencies. In fact, in equation (3.7), each on of the regressors is defined on a specific angular frequency ($k\varpi$) by a linear filter that removes all the unit roots from y_t except the one associated with the specific frequency of the regressor. To check for unit root at zero frequency one can test the null hypothesis of $\pi_1 = 0$ with an unilateral t statistics, comparing the empirical value with the same critical values reported in Dickey and Fuller (1979). Unit root hypotheses at the seasonal frequencies $k\varpi$ ($k = 1, 2, 3$) imply that both statistics associated with the same frequencies are zero ($\pi_{2k} = \pi_{2k+1} = 0$). This can be tested using two sequential t-statistics or a joint F-statistics that, according to Ghysels et al. (1994), presents better statistical properties. Critical values for both the approaches, calculated by a Monte Carlo experiment, are reported in Rubia (2001).

From these findings it can be concluded that stationarity (both at zero and at seasonal frequencies) cannot be considered a general feature of all electricity markets outcomes time series and, on the contrary, must be considered carefully case-by-case before undertaking any empirical analysis. Furthermore, there is not yet an acknowledged methodology to handle (i.e. test) this issue in the electricity markets framework, due to the presence of many specific aspects (seasonality, heteroskedasticity, mean-reverting spikes) that affect the standard procedures and create an unique environment for the researcher. In this situation a preferred strategy would be to consider the process as non-stationary until it is not verified a strong evidence in the other sense, since doing the opposite is potentially more harmful from a statistical point of view (Hendry and Jusielius, 2000). The choice is indeed rather controversial, and must follow economic theory as well as statistical validity. It can be stated that the preference should depend at least on two key elements: first of all the structure and the behaviour of the market investigated and second, but not less important, the time frequency and the time span selected for the analysis. This aspect is further considered in the modelling approach proposed in chapter 5.

3.2.3 Price modelling and forecasting

With the liberalisation of the electric sector, accurate load forecasts are no longer sufficient for the electric utilities. In order to bid optimally into the power pool and to efficaciously engage in bilateral contracts, market participants need also sensible price forecasts. Furthermore, accurate price modelling is fundamental for derivates evaluation and risk hedging. This activities are crucial in the context of electricity markets, given the high volatility which characterise the dynamic of the price of this commodity (see previous section and, among others, Misiorek and Weron 2006). This task proves quite challenging since, as showed previously, electricity price displays characteristics which differ completely from those of other commodities. For instance, a recent issue of *Studies in Nonlinear Dynamics and Econometrics* (2006) has been dedicated to the "nonlinear analysis of electricity prices". The contributions include regime-switching models (Haldrup and Nielsen 2006, Misiorek et al. 2006, De Jong 2006), wavelets (Stevenson et al., 2006) and spectral analysis (Hinich and Serletis, 2006).

One of the features that have caught the attention of many modelers is the presence of sudden spikes (figure 3.7). This characteristic is common in most markets, and it is connected with the attributes of the commodity electricity. Specifically, there are at least two factors which may determine those high and mean-reverting prices: the impossibility of economically storing electricity and the low short-term elasticity of demand. These two conditions may allow strategic bidding by some of the producers which can result in producing extremely high prices for very short periods of time (like one or two hours). This behaviour does not necessarily imply presence of market power and, on the contrary, can even produce beneficial effects on the sector, boosting investment in new generation capacity, as it is showed in Stridbaek (2006) for the Australian market.

Price spikes have been modelled primarily with jump-diffusion processes, for instance in Deng (2000) and Knittel and Roberts (2005). As showed, among others, in Hamilton (1994) a jump-diffusion process can be written as a mixture of two normal distributions. Indicating with p_t the price of electricity at time t and with λ the probability of observing a spike, one can write the conditional (to the first observation) likelihood function that correspond to an AR(1) jump diffusion model as:

$$L(\theta) = \prod_{t=2}^{T} \left[(1-\lambda) N\left(p_t - [\alpha + \phi p_{t-1}]; \sigma\right) + \lambda N\left(p_t - [\alpha + \phi p_{t-1} + \mu]; \sigma + \delta\right) \right] \ ,$$

with:

$N(.)$: normal density probability function;

$\alpha + \phi p_{t-1}$: conditional expected value if there is no spike (probability $1-\lambda$);

$\alpha + \phi p_{t-1} + \mu$: conditional expected value if there is a spike event (prob. λ);

δ: change in variance when there is a spike;

$\theta = [\lambda, \phi, \alpha, \sigma, \delta, \mu]$ parameters that can be estimated, for instance, through maximum likelihood.

The main problem of this specification is that it does not consider that in the electricity price dynamics the jump effect dies out rather quickly and does not lead to sustainable high price levels. One may therefore expect that a sudden jump will be shortly followed by a down-jump. This feature is taken into account in the model proposed by Huisman and Mahieu (2003). They propose a regime-switching model with three regimes: (1) normal price, (2) initial jump and (3) post-jump reversion towards the normal level. Regimes (2) and (3) can last only one period. On the other hand, as pointed out in De Jong (2006), this approach has the drawback of not allowing for multiple consecutive spikes, which are sometimes observed in electricity markets. For this reason, building on De Jong and Huisman (2003) he proposes a model with two indipendent regimes, a 'normal' mean reverting regime and a spike regime Poisson process. In this specification, price does not need to be "pulled down" after a spike simply because the two regimes are indipendent.

The switching probability λ can also be specified as a function of the market fundamentals, such as load generated on the system and available excess capacity (see section 4.1 for more information on this), as it has been done in Mount et al. (2006). They show that this information is crucial to correctly evaluate the switching probability, and can be used in order to effectively predict the spike component. On this point it is important to note that producing accurate load and particularly margin day-ahead forecasts is a necessary input for the analysis.

Load and margin have been used also to develop econometric models in order to describe price dynamics (Karakatsani and Bunn, 2005a) and price volatility (Karakatsani and Bunn, 2005b). The model proposed in the first paper, in particular, contains a detailed non-linear specification of the effects of load on price, including six variables derived from the original traded quantity (namely linear and quadratic polynomials of demand, demand slope and curvature, demand variation, demand volatility). Since the model is constituted by a single equation, the implicit assumption is the weak exogeneity (according to Engle et al. 1983) of the traded quantity. This postulation is still controversial and would imply a perfectly inelastic demand curve, at least in the short term. This ‘demand elasticity dilemma’ is fully uncovered in section 4.3, whereas the model presented in chapter 5 is be used, inter alia, to give new insights on the issue.

Numerous models have been proposed and tested for price forecasting. The mainstream approach has been to extend the techniques developed for load forecasting (see section 3.1.2) to the price time series. A comparison of different methodologies can be found in Bunn and Karakatsani (2003), Conejo et al. (2005) or in the textbook by Weron (2006). Surprisingly, the best predictions are in general obtained with rather simple models, such as ARIMA, ARIMAX (Contreras et al. 2003, Zhou et al. 2006) and transfer function models (Conejo et al. 2004). The explanatory variables considered are in general load or forecasted load and margin (excess capacity). This choice implicitly assumes the strong exogeneity of these variables, allowing the researcher to develop a single equation model without any loss of relevant information (see Engle et al. 1983). Indeed, it looks that inserting load and margin in the model equation is likely to improve the forecasting performance of time series models (see Weron and Misiorek 2005, Conejo et al. 2004, Misiorek et al. 2006, for some comparisons). Still uncertain is if those performances could be improved even more relaxing the strong exogeneity assumption and designing multi-equation models for price and quantity. The model presented in chapter 5 is a first attempt in this direction, even though its forecasting ability is not tested here.

Chapter 4

Electricity wholesale markets behaviour

In the previous section, wholesale electricity markets outcomes have been analysed using time series techniques, and some models have been proposed to study their dynamics. Nevertheless, the scope of this thesis is to develop structural model on time series data, i.e. models which embed economic theory and therefore may be used not only for short-run forecasting but also to derive policy relevant conclusions. Following this intent, in this chapter I will first illustrate the economic and technical grounds which ultimately cause the peculiar dynamics showed in the previous chapter. With this purpose, *section 4.1* presents an analysis of the price formation process in wholesale electricity markets from a micro-economic point of view, focusing on the structure of the supply function.

Section 4.2 introduces the competition issue in power markets, and in particular the analysis of market power from the supply side. Given the strategic value of electricity in the production chain, and the transformation of state-owned monopolies into liberalised markets (see section 2.2), the deregulation process raised particular concern on this point. This issue has been, without any doubt, one of the most fertile area of research in energy economics during the last decade. Nevertheless, some questions are still debated. In particular, a controversial issue, which is also crucially relevant for developing dynamic models (section 3.2.6) for prices, is the elasticity of the aggregated demand function. As showed in *section 4.3*, this is a fundamental point in both theoretical models and in empirical applications. Nevertheless, few attempts have been made to measure it and its value is still and unresolved dilemma. The model illustrated in chapter 5 is designed, inter alia, to give significant insights on this issue.

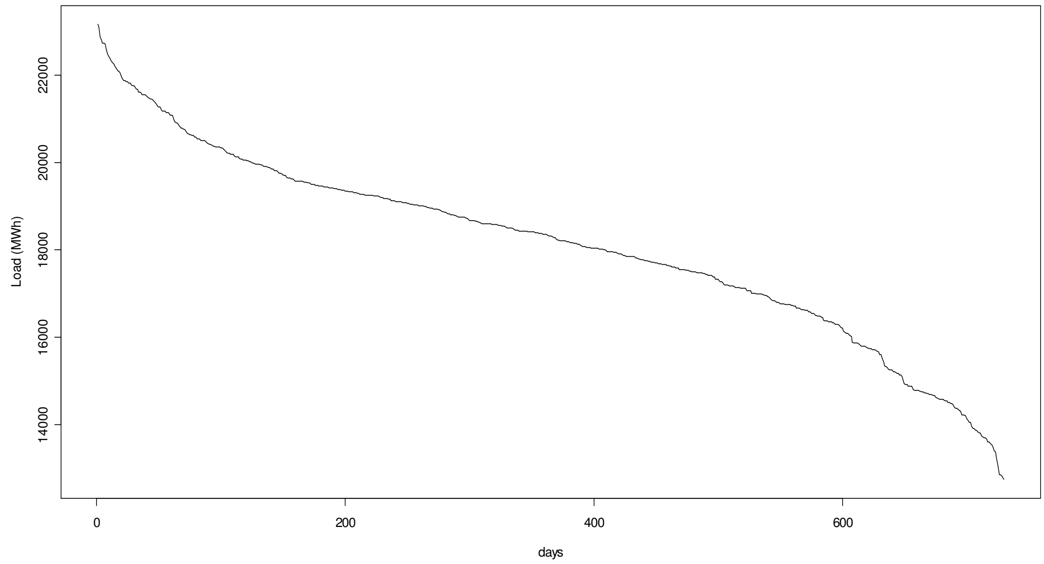
4.1 The price formation process

As introduced in chapter 2.3, the deregulation process has boosted the introduction of wholesale markets: physical and financial exchange points, where electricity is traded both in spot and future contracts . Nevertheless, as showed in the previous chapter, electricity prices are quite different in their behaviour and properties to those in other financial and commodity markets and need specifically dedicated modelling techniques. In this chapter I will illustrate why electricity prices are so different.

The crucial feature of the price formation process in spot markets is the instantaneous nature of the product (Bunn, 2003). The physical laws that determine the delivery of power across a transmission grid require a synchronised and continuous energy balance between production and consumption, without any capability of storage. Furthermore, end-users treat this product as a service at their convenience. The task of the grid operator, therefore, is to continuously monitore demand and to call on those generators who have the technical capability and the capacity to respond quickly to its fluctuations. In figure 3.2 it was showed the annual range of daily demand profiles for California and Spain. Through a mixture of good short-term forecasting (section 3.1.2) and scheduling, instantaneous production also follows these demand paths. Indeed, the average variation of production on the daily horizon is quite significant and around the 25%. This variation is even larger if one takes into account the yearly cycle (figure 3.4). Therefore, it is clear that throughout the day and throughout the year, a wide variety of plant will be in action and therefore setting the price at different times. Furthermore, one would expect a diversity of plant on the system for at least two reasons. The obvious one is obsolescence. The more subtle is, again, due to the impossibility of storing electricity in an economically sensible way. The most efficient power plants, with the lowest marginal costs (typically nuclear) operate most of the time, but during the peak hours some of the high marginal costs power plants (typically gas and small coal plants) are necessary to balance the increase in demand. These plants may be operating for only a few hours, and the recovery of their capital cost may have to be achieved setting high prices. Indeed, if one would like to optimise his stock of power plants, he would invest is some capital-intensive, low operating cost plants to serve the baseload and some relatively expensive to run plants, available for the peaks. This is the generation structure one observes in real power markets, with the consequence that prices are much higher during demand peaks.

The reason for this diversity of plants can be better illustrated deriving a load

Figure 4.1: Daily load duration curve, Spain, 1st of January 1998 - 31st of December 1999



duration curve (figure 4.1). This plot displays the number of days of the year for which the daily average load is greater than a particular level, and it has been derived sorting the data displayed in figure 3.4 (a load duration curve on hourly basis would, of course, display a variation even greater). From the figure it is apparent that, for instance, for 5% of the year the average daily loads are greater than 22 GW. In other words, the owner of a peaking plant with high marginal costs, that would know that 22 GW of capacity on the system can be offered at a cheaper price to the market, would expect to run its plant only 5% of the time (in other words the loading factor of the plant is 5%). Obviously, this is a sensible investment only if the plant can grant substantial margin over the running costs. That is the reason for price to become spiky at the peaks.

It is important to note that the diversity of power plants is a condition which is required in the market by economic reasons. Following Bunn (2003), one can consider a

	Investment cost p.y. (e/KW)	*Marginal Production Cost (e/MWh)*
Nuclear	90	2
Coal	45	10
Gas	20	30

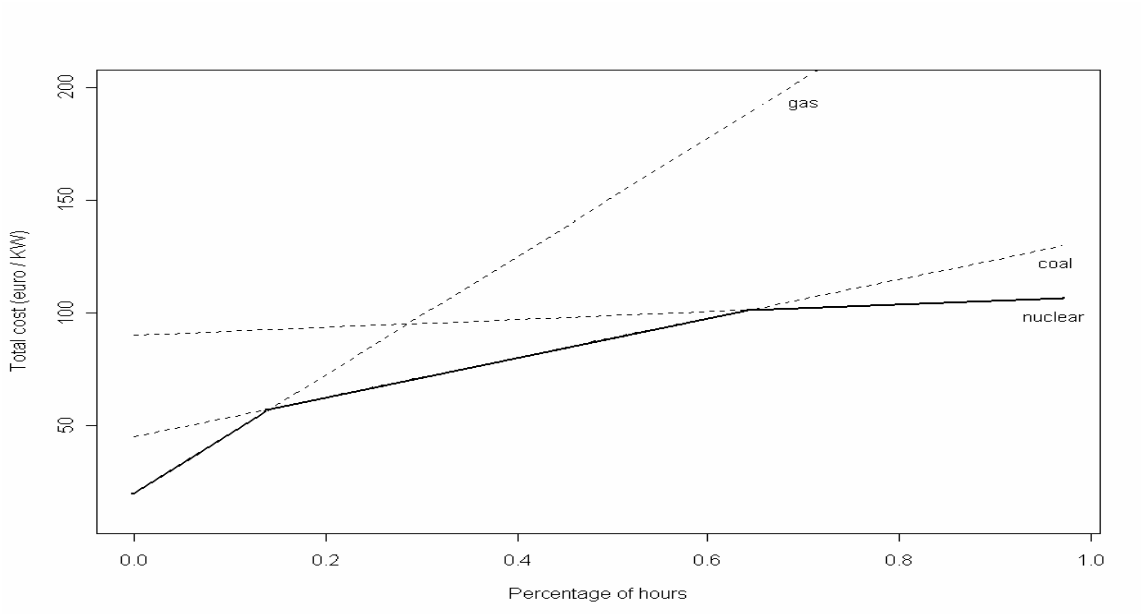
Table 4.1: Technology choice in a simple example

simple example with a set of three technologies with different investment (fixed) cost and operating (marginal) cost. Assuming that the cost of the investment can be spread over the life of the power plant, one can calculate the investment costs per year as reported in table 4.1 and derive the break-even function showed in figure 4.2. According to this simple structure, the nuclear plant needs to run more than 5600 hours per year to be a better investment than the coal one, and only more than 2500 to be a better investment than a gas fired power plant.

In order to find the optimal mix of technology for the Spanish power market, one can just project the break-even analysis onto the load duration curve in figure 4.1. In this situation, nuclear would provide baseload, with 17500 MWh installed, coal power plants would have a capacity of 3000 MWh, and peak load would be covered by gas, for a total capacity of 3500 MWh[1]. Of course a real power system would require some more capacity to secure electricity supply in case of extraordinary peaks of demand or temporary plant outages. From this example one could also derive the supply function offered on the power market, i.e. the stack of marginal costs for each capacity. "The shape of the supply function is one of the most important fundamentals in understanding the behaviour of electricity

[1]For ease of illustration the optimal installed capacity is calculated here using the daily load duration curve. A proper analysis would require at least an hourly load duration curve, which is in general much steeper. In this case the optimal installed capacity for gas and coal would increase, whereas there would be a decrease in the nuclear one.

Figure 4.2: Break-even analysis, straight line = least cost solution

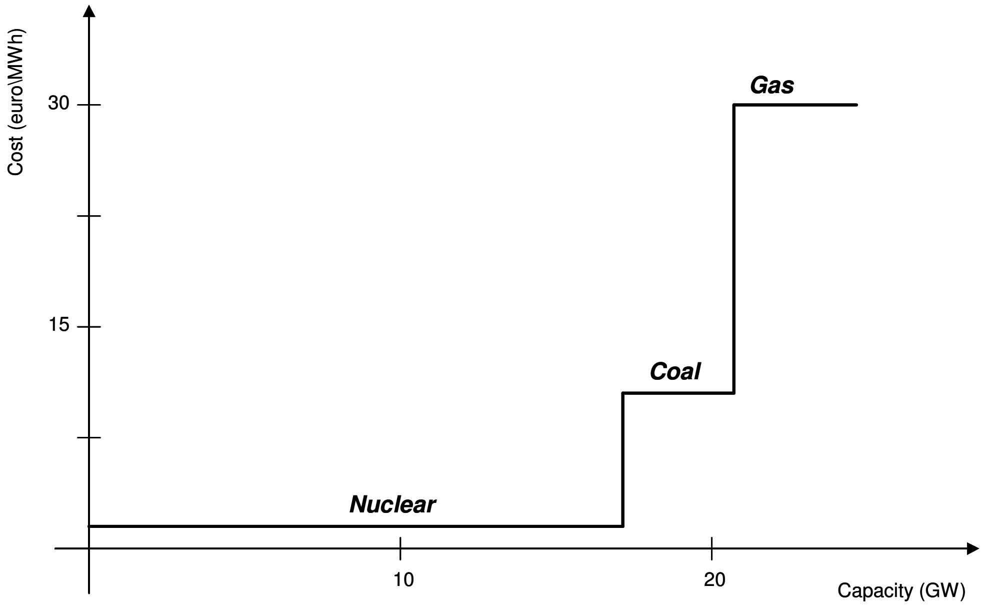


prices" (Bunn, 2003). It is typically a step function, which displays the marginal cost of producing electricity at a particular level of demand[2].

Figure 4.3 plots the marginal cost supply function for the example introduced in table 4.1. Taking into account the high demand variation during the day, the resulting price volatility would be even higher, considering the amplification effect that the steeply-increasing supply function produces (see also the examples in section 3.2 and the empirical analysis in section 5.1.1). In a real system the supply function would present many more steps (for instance, many different technologies, with different investment and marginal costs can be available to produce electricity from gas) and, as a result, it would appear much smoother, but the key features remain the same ones. There are also technical reasons that justify a diversity of plants on the system and, as a consequence, of marginal costs.

[2]This definition assumes perfect competition. The issue of imperfect competition and market power from the supply side is analysed in the next chapter.

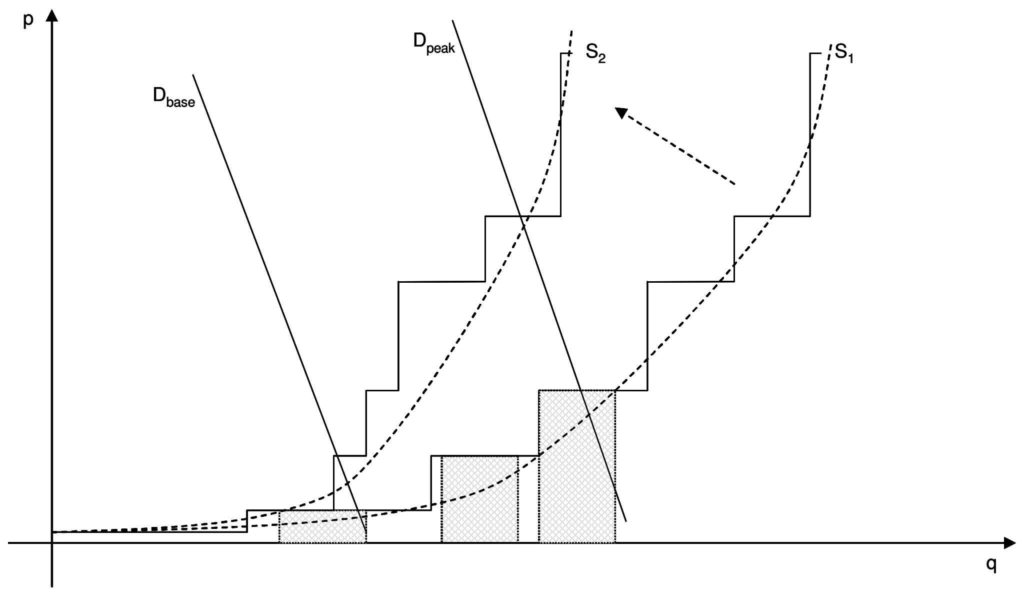
Figure 4.3: Marginal cost supply function for the optimisation example in table 4.1



In fact, some technologies can respond to changes in demand quicker than others. For instance nuclear plants need to run at a constant pace. Small gas and coal plants can, on the contrary, follow the load path more rapidly.

Another fundamental aspect to consider when analysing electricity market outcomes is the excess capacity available on the system, i.e. the amount of power plants willing to produce (and bidding into the market) in a specific hour or day. This is often indicated with the term "margin" and can vary a lot during the year, according to the maintenance schedule of power plants but also to the strategic interaction of the suppliers (see next chapter, Borenstein and Bushnell, 1999 and Borenstein et al. 1999). The impact of the variation of margin on prices is substantial. As showed in figure 5.3, for instance, the same quantity produced can be mapped into very different clearing prices on the market. In fact, as showed in figure 4.4, when some power plant bids are missing (represented by the

Figure 4.4: Shift in the supply curve when some plants (shaded area) are not available to produce, with two different demand curves (baseload and peak)



shaded area) the overall supply curve shifts upwards. This effect is, in general, particularly relevant in peak hours.

Although a substantial amount of electricity is generated from hydro and nuclear sources in various part of the world, the dominant production process is still thermal conversion of fossil fuels, such as gas, oil and coal. This is a very capital intensive process, with surprisingly few workers actually being employed at the power plant (Bunn, 2003). Thus, as electricity is often traded on exchanges one day (or even one hour) before the delivery (see section 2.3), the variable cost of power generation is essentially the fuel cost. With the liberalisation of the gas sector, and the introduction of trading hubs where this commodity is traded on daily basis, also gas volatility has increased rapidly. Recent events have showed how gas price in Europe may be sensible to external factors or simply how it may increase in a very cold winter, when the supply-demand balance is tight. Since an important part of the electricity supply stack is provided by gas-burning power plants, these variations are likely to be passed-through in the power sector. As showed in figure 3.8, the gas-electricity price relation is already strong in the UK market, probably the most mature energy market in Europe.

It is important to note that differences may arise between the marginal cost supply function and the actual market supply function, given by the aggregation of the supply bids offered into the market. Strategic interactions and market power are still present in some markets across the world, and strong regulatory intervention is sometimes necessary to keep prices close to competitive levels. The issue of market power has indeed raised a great interest in the context of electricity markets, particularly because the deregulation process is still at a young stage in many countries (among others also in Italy) and because of the strategic importance of the commodity electricity. The issue of generators market power is the focus of the next section.

4.2 Competition and market power

Until recently, electricity was a monopoly in most countries, often owned by the government, and, if not, highly regulated. During the 90s, ownership has generally become private rather than public and the whole sector has been interested by the process of liberalisation (see section 2.2). The generation sector, in particular, has been progressively deregulated and public-owned companies split in a sufficient number of private firms in order to ensure competition. The main reason for the broad diffusion of this process is that policy makers believed that liberalisation would impose market discipline, encouraging market entry and thus lead to lower production costs, more efficient investments and lower consumer prices.

Unfortunately "the promises of restructuring have not always been realised" (Mansur, 2003). In liberalised markets, price variation has skyrocketed: as illustrated in section 3 a 30% variation on the daily horizon is the average in many markets. As showed in the previous section, this huge price volatility is not necessary a symptom of market malfunctioning. On the contrary, it is often present even in the most competive markets and is connected with the inner structure of the electric system. In particular it is due to (1) the impossibility of storing electricity in a economically feasible way, (2) the continuous demand-supply balance, (3) the presence of different production technologies. Nevertheless, the potential to exercise market power is often present from the supply side. Initiatives to mitigate market power and pursue market efficiency are indeed among the most delicate and debated issues concerning the deregulation process in many countries. This issue is particularly interesting because the exploitation of market power can significantly erode the consumer benefits that would be expected to result from the transition from regulated to competitive markets for electricity generation. The importance of electricity for the whole economy, therefore, motivated the huge amount of research dedicated to this topic in the last decade. As illustrated in the next pages, the novel modelling approach proposed in chapter 5 can give important insight also in this branch of literature.

As introduced in section 2.3.2, the Californian market collapse is probably the most exposed case of market failure. Beginning in summer 2000, the electricity price in California began to rise, reaching peaks of 800 \$/MWh, threatening the financial stability of the state and ultimately leading to the closure of the Californian Power Exchange. The extent to which this huge increase could be attributed to market fundamentals (such as growing production costs or scarcity of generation capacity) or to market power is a crucial issue in order to design better policies and avoid the replication of such cases. On this point, Borenstein et al. (2002) and Wolak (2003), analysing detailed input and production costs, find that at least 50% of the electricity prices in California could be attributed to market power.

Unfortunately, despite its importance for regulatory purposes (for instance to evaluate merging or acquisitions proposals), evaluating market power in electricity markets *ex-ante* it is not an easy task. In fact, the general concentration measures (like the Henfindahl-Hirschman index[3]) implemented in classical industrial economics and traditional measures of price-costs mark-up (for instance the Lerner index[4]) may be inappropriate in the electricity market context (Borenstein et al. 1999, Bower 2004). Indeed, Stoft (2002) argues against applying the HHI to the electricity industry because it ignores some key factors that are crucial in this context: (1) demand elasticity, (2) style of competition, (3) forward contracting, (4) vertical integration of firms, (5) geographical structure. Furthermore, as noted in Borenstein et al. (2002) and Fabra and Toro (2005), given the non-storability of electricity, market power can exhibit huge inter-temporal variations.

The main techniques proposed to measure the potential for suppliers to exercise market power in electricity markets can be divided into three main approaches (Knittel and Roberts, 2005). The *first* one relays on simulating through a game-theoretical model

[3]The HHI is defined as: $HHI = \sum_{i=1}^{n}(s_i)^2$, with s_i market share of the firm i.

[4]The Lerner index is the typical measure of price - costs markups and it is defined as: $(P_t - mc_t)/P_t$.

the strategic behaviour of the firms and compare the outcomes with perfectly competitive prices. The most diffuse models have been Cournot oligopoly (Andersson and Bergman 1995, Borenstein and Bushnell 1999, Borenstein et al. 1999, Lise et al. 2003) and supply function equilibrium model (Green and Newbury 1992, Green 1996, Baldik et al. 2004). In both approaches, the price is determined by the intersection between the (simulated) supply and the demand curves. As showed in the chapter 4.3, specifying the demand curve in electricity markets is not an easy task, due to the low short-run elasticity. Indeed, often the results of these analyses are presented under different assumption for the price elasticity of demand.

A *second*, more direct, approach is to compare hourly engineering marginal costs with actual market clearing prices. Wolfram (1999), for instance, compares market prices to marginal costs for the restructured UK market finding that prices, even though higher than in a perfect competitive regime, are lower than implied by game theoretical models. Possible explanations are that firms are facing regulatory constraints and the threat of entry. Other contributions are Borenstein et al. (2002) and Joskow and Kahn (2002), where California electricity market prices are compared to marginal costs. Both papers find that mark-ups over marginal cost increased during the summer 2000 crisis period. Again, these analyses often rely on assumptions regarding the elasticity of demand to price. Furthermore, as pointed out in Mansur (2003), in these approaches it is important to consider that electricity generating units often are subject to production constraints. After taking into account cost non-convexities (such as power plants start up costs) he shows that PJM prices in the years 1998-99 were, on average, only 3% above perfectly competitive levels (and not 12,5% higher as one would conclude ignoring production constraints).

The *third* methodology studies the dynamic interactions of agents by simulating market behaviour at a microscopic instead of at an aggregated market level. These agent-based models allow for heterogeneous utility functions, non-linear trading rules, learning modes and detailed representation of the market environment. They often focus on agent interactions after a regulatory intervention to the market, such as the introduction of new trading arrangements (Bower and Bunn 2001, Bunn and Oliveira 2002) or CO2-emission trading and the intensified application of renewable energy sources (Veit et al., 2004). In this *ex-ante* framework, the models derive acting recommendations for market participants as well as political and regulatory authorities. Nevertheless, the parameter validation and the results' sensitivity to them are two substantial sources of complexity.

There have also been a few studies implementing *econometric approaches* to estimate, on time series data, the actual level of market power. Hjalmarsson (2000), for instance, extends to the dynamic case the static Bresnahan-Lau (Bresnahan 1982, Lau 1982) model for the identification of market power. This method leads to estimate a parameter, which varies between 0 (perfect competition) and 1 (monopoly) and encompasses how far the actual price is from a perfectly competitive situation. As showed in detail in the next section, also this approach requires rather subtle assumptions on the shape of the demand curve. According to this study, the hypothesis of no market power for the Nord Pool (years 1996-1999) cannot be rejected at any reasonable significance level. On the other hand, Fabra and Toro (2005) find substantial evidence of time-varying market power in the Spanish power sector. Accounting for changes in demand and cost conditions (which reflect changes in input costs, capacity availability and hydro power) they show that the time-series of prices is characterised by two significantly different levels. They explain these findings with the possible collusive behaviour of the two Spanish market leaders: Endesa and Iberdrola.

As illustrated, the ex-ante assessment of potential for market power and the actual measure of market power on market outcomes have been subject to extensive research which reflects the crucial importance of these issues on the policy makers agenda. Nevertheless, the results of most of these studies are sensitive to some of the assumptions, particularly regarding the shape of the demand curve. In the next section, the "elasticity dilemma" which characterise the electricity demand function is fully illustrated. This section is particularly significant since the model proposed in chapter 5 is designed to estimate, *inter alia*, this parameter, using wholesale markets outcomes time series.

4.3 The demand elasticity dilemma

The elasticity of demand to price is a subtle issue in the research on electricity markets. Electricity is produced as a commodity, but it is consumed as a service and often end-use consumers do not have incentives to change their consumption patterns according to the short-term variations of price, because not directly exposed to it. On the other hand, recent empirical research (Callaway and Weale, 2005) showed that large industrial consumers can indeed temporarily reduce production or switch to their own back up generators (in both case reducing the overall demand on the market) if electricity prices are perceived as too high.

As pointed out in Borenstein (2004): “electricity demand elasticities are subject to a nearly endless contention”. Nevertheless, investigating this issue is extremely important in the context of electricity markets. In fact, it is a fundamental information for developing theoretical models to address, for instance, market power potentials (section 4.2) and also for designing accurate statistical models for prices (section 3.2.3). Furthermore, demand responsiveness to high prices has been proposed as an effective way to mitigate market power (Borenstein and Bushnell 1999, Borenstein et al. 2002b, Borenstein 2004).

As showed in chapter 3.2, many high frequency empirical models of prices have established relationships with various market fundamentals (i.e. the quantity traded on the market, the available capacity, the fuel prices) to develop conditional models in a single equation framework (see Karakatsani and Bunn 2005a, 2005b, Weron and Misiorek 2005, Mount et al., 2006). Doing so, the quantity traded on the market has been explicitly considered as fixed (i.e. exogenous), assuming a perfectly inelastic demand curve, at least in the short run for high frequency hourly analysis.

For instance, in Karakatsani and Bunn (2005a), high-frequency price dynamics are analysed as a process conditioned to some explanatory variables, among others demand and excess capacity available on the system. The model is used to asses if wholesale British NETA prices were cost reflective during the low prices period 2001-2002. Hence, a structural meaning is given to the parameters of the model. The validity of this inference strongly relies on the assumption of a non-elastic demand curve, as the two Authors acknowledge declaring that: “such regression would be invalid, if demand would not be exogenous”. On the same assumption are founded the models proposed in Karakatsani and Bunn (2005b) in order to analyse electricity price volatility. They found that including covariates in the variance specification is able to capture the 'Arch effect' commonly observed in price dynamics (see, for instance, Duffie et al. 1998, Knittel and Roberts 2005 and chapter 3.2.1) and that a relevant source of risk in electricity price dynamics is connected with demand movements. Again, they note, these results are valid only if "demand is perceived as an exogenous variable, because of the negligible elasticity in the short term". In another study on volatility, Goto and Karoly (2004) find significant Garch effect in the dynamics of PJM, NordPool and Austrialian market. Including in the equation of the conditional mean the quantity traded on the market, they implicitly assume an inelastic demand.

Quantity is included as a deterministic regressor also in the forecasting models proposed in Contreras et al. (2003), Conejo et al. (2004), Rodriguez and Anders (2004), Mount et al. (2006), Weron and Misiorek (2005). In these contributions, the performance of various forecasting methods is compared in performing short term predictions of different power market price series (for instance PJM, Spain, California and Ontario). Not surprisingly, the information included in the quantity time series proves to be fundamental in order to achieve adequate performances. Indeed, according to these studies, the most promising results seems to be the one achieved applying time series techniques such as transfer function methods, ARIMAX and dynamic regression models (section 3.2). These single equation approaches are efficient for forecasting only if the variables on which the equation is conditioned (in this case quantity and other market fundamentals) are, according to the terminology introduced in Engle et al. (1983), strongly exogenous. This assumption is violated if the demand function is not perfectly inelastic, i.e. it is influenced by price

Article	*Market*	*Demand Elasticity*
Borenstein et al. (1999)	California	from 0.1 to 0.4
Borenstein and Bushnell (1999)	California	from 0.1 to 1.0
Borenstein et al. (2002)	California	zero
Green and Newbury (1992)	United Kingdom	from 0.1 to 0.5
Green (1996)	United Kingdom	0.25
Hjalmarsson (2002)	NordPool	elastic
Johnsen et al. (2004)	NordPool	elastic
Lise et al. (2004)	Germany	0.4
Mansur (2003)	PJM	zero
Wolfram (1999)	United Kingdom	0.17

Table 4.2: Assumed demand elasticities in articles analysing market power and strategic interaction of firms in electricity markets

dynamics.

In contrast with those contributions, as showed in section 4.2, often an elastic demand has been assumed in order to analyse the firms strategic interactions and their implications for price and social welfare (in particular measuring the extent of market power). Nevertheless, as showed in table 4.2, there is not an overall agreement regarding the value of this parameter. Furthermore, demand elasticity is almost always a crucial factor and the outcomes of these models are often presented under different assumption regarding its value. For instance, Borenstein et al. (1999) consider the amount of potential market power in the Californian electricity market developing measures which differ from the commonly implemented concentration indexes (like the HHI). Simulating the strategic behaviour of firms as a Cournot oligopoly they found that demand elasticity is a crucial parameter in the electricity price formation process, and that the equilibrium price is much higher when the assumed demand elasticity is lower (they compare a range of values from 0.1 to 0.4). These results are confirmed by the analysis of the restructured Californian electricity market in Borenstein and Bushnell (1999). They show how one of the most important factors in determining the extent of market power is indeed the elasticity of the aggregated demand.

Market power is also analysed in Green and Newbury (1992) using a supply function equilibrium model. Assuming different elasticities of demand (from 0.1 to 0.5) they found that the duopoly implemented during the first years of deregulation in Britain was leaving considerable market power to the two incumbents. An examination of possible policies devoted to address this issue is presented in Green (1996). Using a linear supply function model (with demand elasticity equal to 0.25), the Author finds that the regulator chosen policy (partial divestiture), would lead to a substantial reduction in deadweight losses.

Wolfram (1999) examines electricity prices in the British market, empirically estimating price-costs markups to measure the presence of market power from the supply side and estimating a Lerner index of 0.24. However, much of the Lerner index could be explained by the low elasticity of demand (assumed equal to 0.17) and, after controlling for this factor[5] the average adjusted Lerner index is around 0.05. The results imply that prices, even though higher than marginal costs, where not as high as implied by some theoretical economic models (like, for instance, the ones proposed in Borenstein and Bushnell, 1999 and in Green and Newbury, 1992). Possible explanations are that firms are facing regulatory constraints and the threat of entry.

Also in the econometric study of Hjalmarsson (2000), based on a dynamic Bresnahan-

[5]The elasticity adjusted Lerner index controls for cross-sectional or time series deviations between prices and marginal costs driven by differences in the elasticity of demand. It is defined as $(P_t - mc_t)\eta_t/P_t$, where η_t is the elasticity of demand at time t. As a convenient benchmark, the elasticity adjusted Lerner index for a symmetric Cournot game with N firms is 1/N. Therefore, Wolfram (1999) results suggest the market is acting as if there are 20 symmetric firms, whereas there were three major firms, one of which dominated the market with 52% of capacity.

Lau (Bresnahan 1982, Lau 1982) model for the identification of market power, the shape of the demand curve plays a fundamental role. In this framework, in order to identify the market power parameter, not only an elastic demand is required but also variables able to rotate the demand curve (i.e. alter the elasticity) have to be included in the model. With this purpose Hjalmarsson (2002) considers the interactions among price and the demand curve shifters (like the atmospheric conditions) and finds no significant presence of market power in the NordPool. This result is not supported by the analysis of Johnsen et al. (2004), which evidence that Nordic market prices are higher when demand in less elastic. Also according to Borenstein et al. (1999) when demand is less elastic, the possibility to exercise market power from the supply side is higher. Hence, Johnsen et al. (2004) are able to identify price markups comparing the market prices in different periods, specifically when marginal costs are the same and demand elasticity varies. They evidence that some firms have incentives to withhold capacity when transmission constraints bind and hence increase the price. Lise et al. (2003) address the impact on the environment of the electricity liberalisation process in Germany. This study, based on a large simulation model in which demand elasticity is assumed constant and equal to 0.4, shows that, when firms act strategically, the environment is better of at the cost of higher electricity prices.

Even though in most paper belonging to this branch of the literature demand is assumed elastic, there are also notable exceptions. For instance, Borenstein et al. (2002) analyse the presence of market inefficiencies in the Californian restructured electricity market assuming a short term inelastic demand. On the same assumption is founded also the empirical study on market inefficiencies of the PJM market of Mansur (2003). The paper, based on a detailed description of the cost faced by the producers in this market, finds a rather competitive environment. Some of the equations of the econometric set up, in order to maintain structural meaning, require the assumption of a “completely inelastic demand”.

Despite the clear importance of this issue, few attempts have been made to directly measure the value of electricity demand elasticity. Some contributions on demand response to price have focused upon micro survey data, at the company or individual level, (see Patrick and Wolak, 2001, Callaway and Weale, 2005). They found that day-ahead demand elasticity estimates vary substantially by time-of-day, industry, and firms within industries; with sample mean averages ranging from essentially zero to 0.86 in absolute value. Despite clearly giving behavioural insights, these do not help directly in specifying elasticities for the spot and forward trading markets. In contrast, in the next chapter, I seek to addresses this question from the perspective of publicly-available, wholesale day-ahead market data, specifying a dynamic econometric model that encompasses the short-term interactions of electricity price and quantity. This approach allows to directly estimate on time-series data the value of the elasticity of the aggregated demand, and understand in a dynamic framework how quantity reacts to price changes.

Chapter 5

Structural analysis of high-frequency electricity demand and supply interactions

In the previous sections has been illustrated how the assumptions on electricity demand elasticity have been fundamental to at least two lines of research on energy markets. At an initial prospect, unfortunately, these assumptions may appear difficult to conciliate. In fact, developers of dynamic, stochastic models devoted to describe and forecast market price have often assumed an inelastic demand. On the contrary, in economic models, used, for instance, to measure market efficiency or to identify the presence of market power, demand elasticity is often set as different from zero and its value is almost always crucial for the analysis. Nevertheless, few attempts have been made to empirically measure this parameter and no one at all using high-frequency wholesale market data. Therefore, this chapter presents a model that allows to identify and empirically estimate the demand and the supply curves in electricity markets. It can be used, *inter alia*, to give valuable insights on the demand elasticity dilemma, directly estimating this parameter.

The proposed approach is novel, since it is based on high-frequency, public-available, wholesale day-ahead market data. I also advocate that simplifying the complex dynamic response of electricity demand to price into one unique elasticity parameter can lead to misleading conclusions. In the model proposed here, I identify three different ways in which demand may react to a change in price: instantaneously, in terms of an econometrically estimated equilibrium and through an error-correction mechanism. Furthermore, I consider the possibility of asymmetries in the demand response, i.e. demand may react differently to an increase or to a decrease in prices. This feature is consistent with the intuition that, in the short run, large industrial consumers may shut down machineries or switch to their own back-up generators if the electricity price is too high, but may not, under normal circumstances, alter their production patterns substantially if price is lower than expected. The econometric model is specified in a dynamic, simultaneous equation, error-correction form and presents both statistical soundness and economic foundation. The first one is secured because the approach followed in this work is inspired by the methodology advocated in Hendry and Mizon (1993), Johansen and Juselius (1994), Hendry (1995) and Johansen (1996). In other words data are initially analysed developing a well-defined statistical model, and then a downward testing procedure is implemented, in order to derive the structural specification. The economic grounds are preserved since the restrictions are inspired by a general theoretical economic model.

This chapter is organised as follows: in *section 5.1* a preliminary data analysis is presented, with particular focus on the hypothesis of stationarity which, as showed in section 3.2.2, in the context of electricity markets is still debated and may rise subtle issues of specification. In this analysis, for instance, stationarity is not supported by empirical evidence and the variables are modelled as I(1). *Section 5.2* illustrates a theoretical economic model describing the price-formation process in wholesale electricity market (see section 4.1), where the aggregated supply and demand curves are approximated with continuous functions. Thereafter, the model is translated into an empirically feasible, linear specification. In *section 5.3* the statistical methodology devoted to the analysis of I(1) variables is briefly illustrated. The error-correction model and the cointegration methodology (Johansen, 1996) are presented, focusing in particular on the asymmetric case, on the identification problem and on the weak exogeneity test. In *section 5.4* the dynamic version of the model developed in section 5.2 is specified as an asymmetric, error-correction simultaneous system of equations including price and quantity. Synthetically, this model gives us the opportunity to:

i. obtain a robust inference on the relationships among supply and demand securing against the risks of spurious regression and endogeneity;

ii. test structural hypotheses on the supply and demand function and specifically analyse how quantity reacts to price dynamics and vice versa, both in the long and in the short run;

iii. analyse all these features on high frequency (hourly) data, comparing the structural differences that characterise distinctive hours of the day.

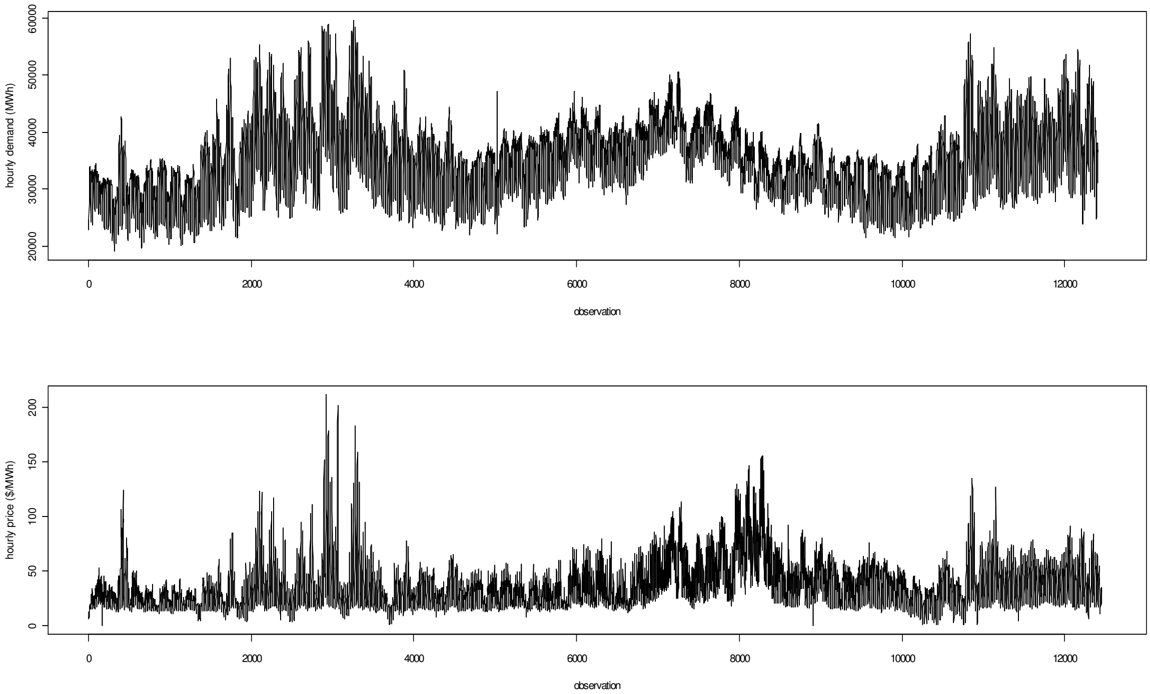
In *section 5.5* the model is empirically estimated on the electricity wholesale market data analysed previously. *Section 5.6* concludes.

5.1 Preliminary data analysis

The methodology proposed in this chapter is empirically estimated on PJM (Pennsylvania, New Jersey and Maryland) hourly day-ahead market data, spanning a period from 1st of April, 2002 to the 30th of August, 2003. This market, which is one of the most established worldwide, is described in section 2.3.3. As stated in Bushnell et al. (2004), "the PJM market has been widely viewed as the biggest success amongst US markets". Furthermore, most market data are public available, and can be easily accessed on the internet site of the independent system operator: *www.pjm.com*. For these reasons this market has been subject of extensive research (see, among the most recent contributions, Mansur 2003, Longstaff and Wang 2004, Wolak 2004, Conejo et al. 2005, Mount et al. 2006). In the PJM day-ahead market are currently active more than 300 entities, which mainly operate both as buyers and as sellers. This framework ensures the system a good level of competitiveness and reliability (Market Monitoring Unit, 2004). In the period considered in the analysis the generation capacity consisted of approximately 76.000 MW, including hydro, nuclear, coal, natural gas and oil. Nuclear and coal plants provided baseload generation, producing most of the quantity, whereas gas and oil plants were active mainly in the peak periods.

Given its large dimensions, the market has been divided into different zones implementing a zonal price system. For this reason, when transmission constraints are present, the marginal price can differ among zones. Nevertheless, in this analysis it is considered

Figure 5.1: Quantity (MWh) and price ($/MWh) traded on the PJM market, from the 1st of April, 2002 to the 31st of August, 2003.



only the price on the market as a whole, i.e. the weighted average of the hourly zonal prices. In section 5.1.1 is presented a descriptive analysis of the data used to empirically estimate the model proposed later in this chapter, in section 5.2.2 particular emphasis is placed on the stationarity hypothesis which, as showed in section 3.2.5, is a subtle issue in the context of electricity markets outcomes time series.

5.1.1 Descriptive analysis of PJM electricity market outcomes

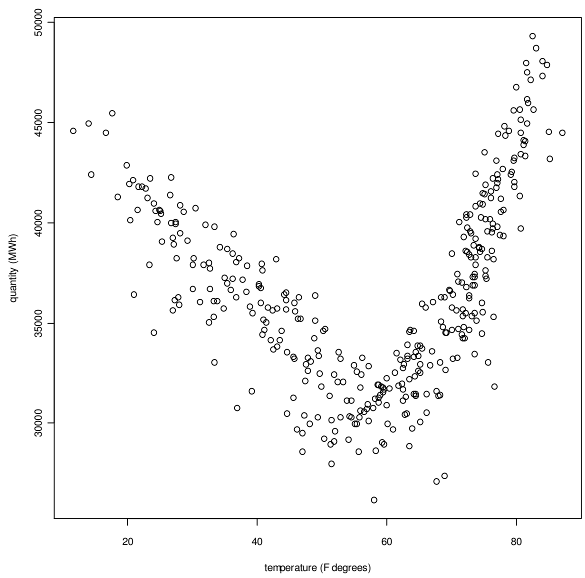
Electricity market outcomes and their peculiar dynamic properties have been presented in chapter 3. In this section it is showed how PJM day-ahead market results display the distinct features of electricity markets price and quantity time series. Therefore, this data represent a good framework to empirically estimate and evaluate the model proposed in the next sections. Market outcomes (quantity and price) high-frequency time series are showed in figure 5.1.

The quantity series displays the typical annual seasonality, with two peaks per year (winter and summer). As illustrated in section 3.1.1, these dynamics are related to the atmospheric conditions, that in general exhibit a smooth variation all through the year. Nevertheless, quantity dynamics are different in the two peak periods. In fact, the summer peak is characterised by a high variability (its peak is higher and its dip is lower than the winter ones) whereas in the winter peak the increasing in electricity consumption is not followed by an increasing in the variance. This difference reflects how the marginal drivers of electricity consumption (cooling and heating) are inherently different in the two peaks.

The strong relationship among electricity usage and temperature can be showed also through a scatter-plot, as the one reported in figure 5.2. The relation among quantity and temperature is 'V' shaped with the two intercepting lines presenting different slopes. Hence, electricity consumption increases differently with cold or warm temperature. This feature implies that, approximating this relation with a second degree polynomial, (which implies symmetry) is probably not the most appropriate choice. This issue is further considered in developing the empirical specification of the model (section 5.2).

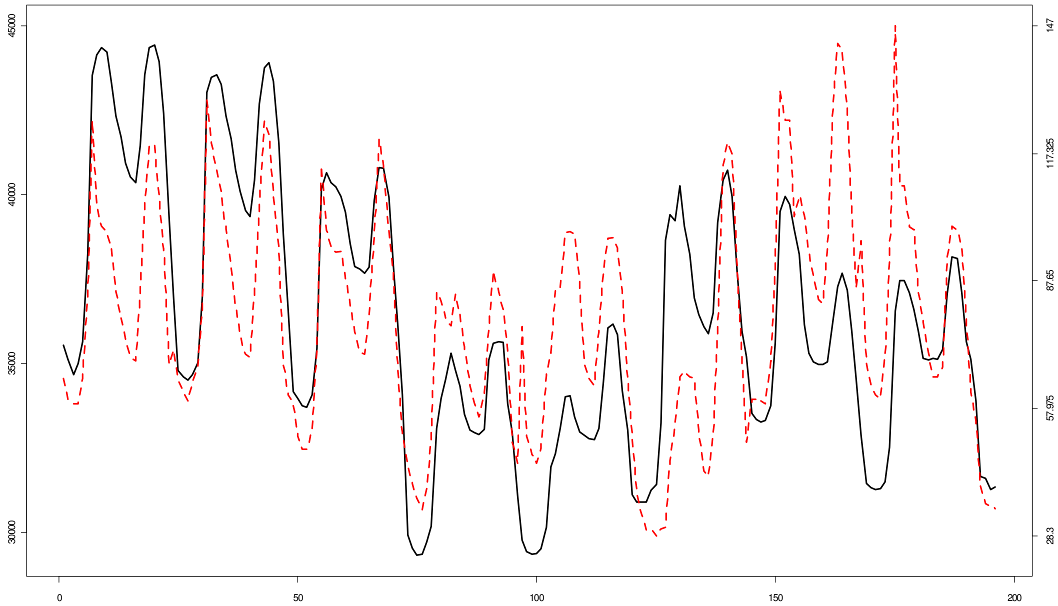
Going back to figure 5.1, it can be noticed how electricity price dynamics are strongly linked with quantity movements. High-prices are more frequent during the summer, whereas, when demand is lower, (typically in spring and autumn) prices are more stable and constantly under the 100$/MWh threshold. Price dynamics are not always mimicking

Figure 5.2: Scatter plot between PJM average quantity (MWh) and atmospheric temperature (F0), from the 1st of April, 2002 to the 31st of August, 2003.



quantity ones, but also present distinctive characteristics, as can be noticed observing figure 5.3. In the picture are showed in detail the hourly prices and quantities during 9 days of trading, from the 26th of February to the 5th of March 2003. To the highest price in the graph (147 $/MWh) corresponds a moderate quantity, which is about one third lower than the highest quantities in the sample (which are traded at lower price, around 115$/MWh). The reason for those large differences cannot be ascribed to the demand elasticity since, as illustrated in sections 4.1 and 4.3, its value is too low to cause such a disparity. As showed in section 4.1 and 4.2 not only demand but also supply shocks play a fundamental role in the price formation mechanism. For instance, when the available capacity (margin) is different, the same amount of electricity can be traded on the market at completely different prices. The situation showed in figure 5.3 is a typical example of such cases.

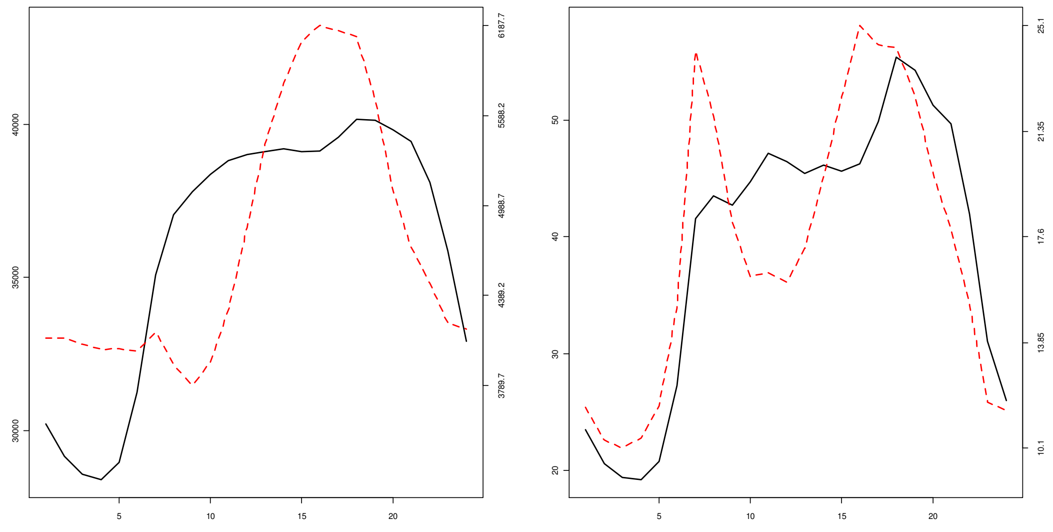
Figure 5.3: Quantity (straight line, MWh) and price (dotted line, $/MWh) traded on the PJM market, from the 26th of February, 2002 to the 5th of March,, 2003.



In the plot it is also evident the seasonality characterising market outcomes on the weekly and on the daily cycle. As illustrated in section 3.1.1, both seasonalities are connected with the working and living habits of the population. As showed in the following sections, in this context the weekly cycle can be eliminated with no significant loss of information simply dropping the weekends from the analysis (the same approach has also been implemented, for instance, in Ramanathan et al. 1997).

Daily seasonality is quite relevant: for both series strong differences subsist among distinct hours, as can be noticed comparing hourly means and standard deviations in figure 5.4. As expected, the difference on daily basis is substantial: a 30% variation for quantity and a 150% one for price. The reason for this high price variation has been illustrated in section 4.1. Since electricity demand presents usually a high variability on the daily horizon,

Figure 5.4: Hourly means (straight line) and standard deviations (dotted line), PJM clearing quantity (left) and price (right), working days only.



every power market needs low marginal cost generation units operating all day (usually with high start-up costs) and flexible plant, typically with higher marginal costs, producing only in the peak. This feature creates an extremely high price volatility on daily basis since, when the quantity produced varies, different plants start to produce and the pivotal technology (and hence, the marginal cost) changes. For this reason has been argued that, for modelling purposes, electricity traded in different hours should be considered as different commodities (Guthrie and Videbeck, 2002). Consideration of this sort, as illustrated in chapter 3.2.3, have inspired methodologies based on estimating separate models for each hour of the day. Since the innovative work on quantity forecasting of Ramanathan et al. (1997), this approach became rather established in both quantity and price (see the reviews in Bunn, 2000 and Bunn and Karakatsani, 2003) time series models.

This choice is conform to the mechanism implemented in most day-ahead wholesale

	$\bar{x}$	$\hat{\sigma}$	CV	*skew.*	*kurt.*
Quantity H24 (MWh)	33415	4442	0.133	0.26	2.18
Quantity H19 (MWh)	40772	6352	0.156	0.49	2.71
Price H24 ($/MWh)	25.17	11.16	0.443	2.42	11.65
Price H19 ($/MWh)	52.87	24.24	0.458	1.20	4.89

Table 5.1: Descriptive Statistics

markets across the world (among others in PJM), where electricity is traded in separate and concurrent auctions for each hour of the subsequent day (see section 2.3 for some examples). Following these considerations, in the next sections the empirical estimation of the econometric model will be implemented considering market outcomes of different hours as separate time series.

In order to evaluate the model in two distinct contexts, a baseload (hour 24) and a peak hour (hour 19) are selected. The baseload hour is characterised by lower price variability and by marginal generating plants constituted primarily by nuclear and large coal plants. On the contrary, the selected peak hour presents the highest volatility of the sample and has gas-fired power station as typical marginal generating units. The descriptive statistics of market outcomes time series in the two hours are reported in table 5.1[1].

The difference between the two hours is substantial, even though there is a consistent overlap between the quantity densities, due to the strong yearly seasonality. A movement in quantities echoes amplified in prices, as can be noticed comparing the coefficients of variations. This feature is not surprising since, as illustrated in section 3.2, electricity prices present a high volatility and sometimes show idiosyncratic and unexpected movements. For

[1]Shewness defined as the third standardised moment: $skew = \mu_3/\sigma^3$, where μ_3 is the third moment about the mean and σ is the standard deviation. Kurtosis defined as the fourth standardised moment: $kurt = \mu_4/\sigma^4$, where μ_4 is the fourth moment about the mean.

these reasons this time series is, by far, more difficult to predict than the quantity one. Moreover, price distributions are quite distant from the Gaussian one, a problem which, in the rest of the analysis, is somehow reduced applying the logarithmic transformation.

All the time series used in the empirical specification of the model, presented in the next sections, are plotted in figure 5.5. These include available excess capacity, electricity prices and quantities for hour 19 and 24, downloaded from the internet site of the PJM Interconnector, atmospheric temperature (measured as the daily average between the Pittsburgh and the Philadelphia ones) provided by the University of Daytona Archive, gas price (traded on the Henry Hub) available on DataStream and coal price (Pennsylvania coal price index) available on Bloomberg. Discarding the weekends, the total amount of observations for each series is 370. PJM day-ahead market results present the same drifting behaviour observable on the complete series in figure 5.1, i.e. a smooth yearly seasonality connected with the variation of temperature. These dynamics are even more evident when the daily and weekly seasonalities have been filtered from the data, eliminating the weekends and selecting only one hour of the day. The two fuel prices present complete different dynamics. Coal price is quite stable during the all sample, whilst gas price is characterised by a high spike during the end of February 2003. This feature was caused by a conjuncture of low supply and high demand, originated by a particularly cold winter.

As in general it happens when electricity market data are analysed, observing those graphs it is not easy to decide regarding a delicate issue like the stationarity of the time series. This feature can be investigated also observing the autocorrelation plot of the market outcomes in hour 24, plotted in figure 5.6[2]. The autocorrelations are quite persistent

[2]The autocorrelation function for the market outcomes in hour 19 is extremely similar and therefore not

Figure 5.5: Hourly clearing prices and quantities, PJM day-ahead market, hour 19 and hour 24. Atmospheric temperature, excess capacity, coal (Pennsylvania index) and gas (Henry Hub) prices. Time span: 01/04/2002 – 31/08/2003.

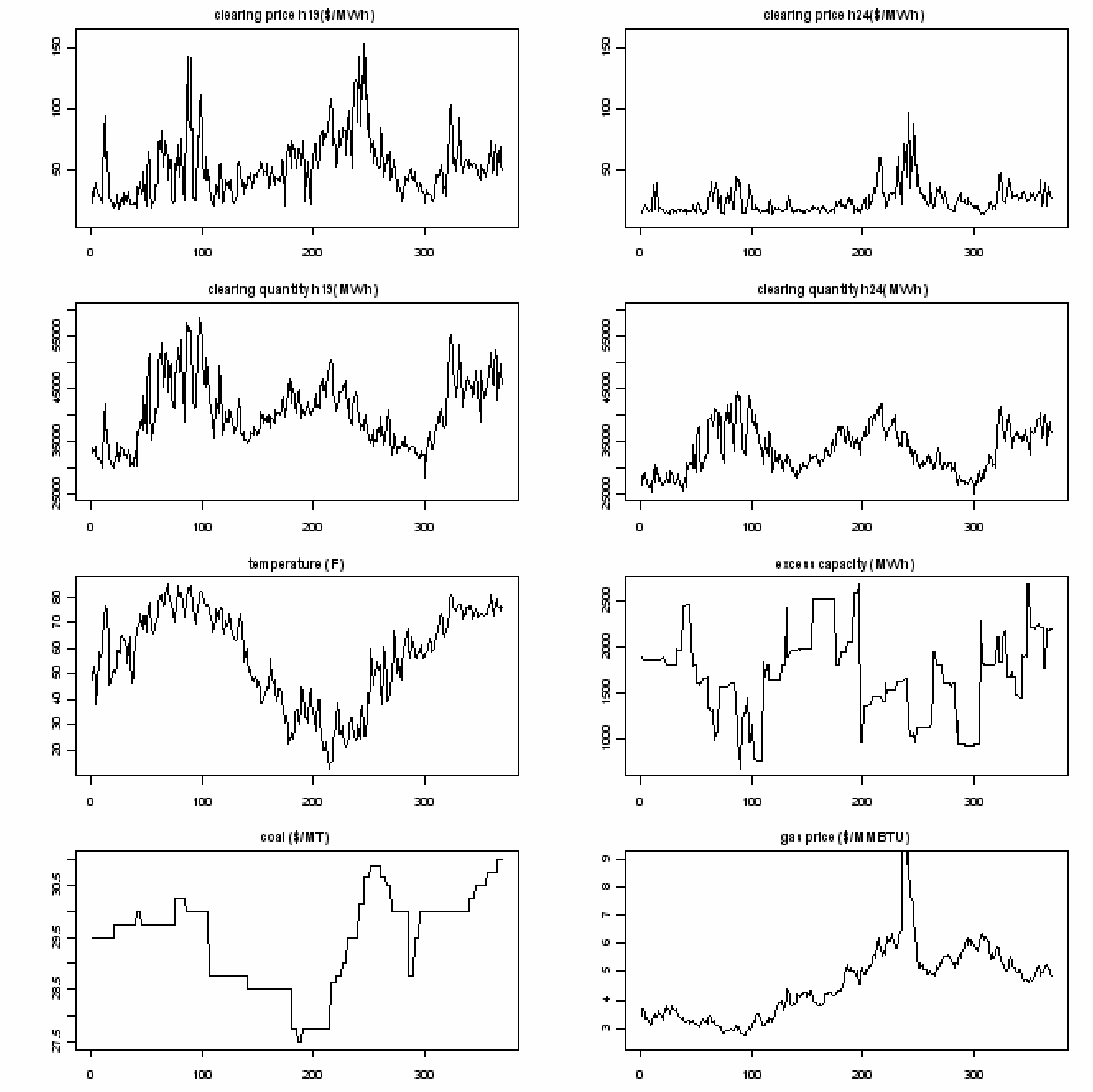
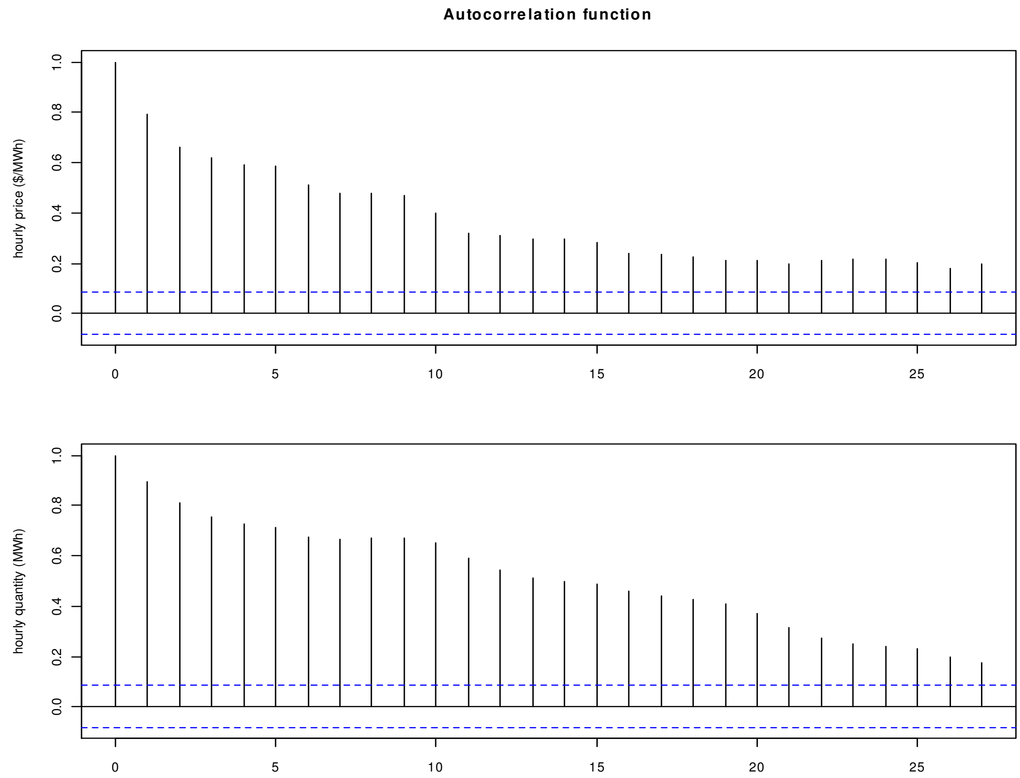


Figure 5.6: Autocorrelation plot for hour 24 price and quantity, working days only.



and do not show the weekly seasonality which has been successfully removed discarding the weekends. The autocorrelation paths are consistent with a process with long memory, either stationary or with unit root. The next section is devoted to the evaluation of this issue.

5.1.2 Unit root and stationarity analysis

In this section the hypothesis of stationarity of the time series modelled in the following parts is empirically evaluated. As illustrated in section 3.2.2, despite its importance for modeling purposes[3], the stationarity of electricity prices and quantities is still an

reported here.

[3]One of the bases of classical econometric theory is the stationarity of the variables considered in the analysis (Hendry and Juselius, 2000). Under this condition classical statistical inference is valid, while assuming this postulation when it doesn't hold can induce serious statistical mistakes, invalidating in most

	ADF	KPSS
Levels		
Q_{19}	-2.40	0.323
P_{19}	-2.80*	1.14***
Q_{24}	-2.47	0.383
P_{24}	-3.08**	1.31***
C	-3.86**	0.219
P_{gas}	-1.84	3.80***
P_{coal}	-1.09	2.56***
Temp	-1.14	0.978***
First differences		
Q_{19}	-12.42***	0.035
P_{19}	-12.61***	0.017
Q_{24}	-6.48***	0.038
P_{24}	-8.03***	0.016
C	-19.56***	0.034
P_{gas}	-9.03***	0.050
P_{coal}	-19.14***	0.178
Temp	-3.93***	0.099

Table 5.2: Unit Root and Stationarity Tests

open issue in the literature. In most analyses (Escribano et al. 2002, Huisman and Mahieu 2003, Karakatsani and Bunn 2005a) price and quantity are modelled as stationary, but there exists notable exception. For instance, Stevenson's (2002) analysis of the Australian electricity prices and the works by Contreras et al. (2003) and Conejo et al. (2005), on PJM. Has also been argued that, for some electricity price time series, neither an I(1) nor an I(0) description is appropriate. On this point Haldrup and Nielsen (2006) develop a fractionally integrated process describing NordPool price dynamics. The proposed process is on the border between stationarity and non stationarity, presenting both long memory and mean reversion.

cases all the inference procedures and leading to a problem known as "spurious regression". See section 3.2.5 for an illustration in the context of electricity markets. For a detailed and extensive analysis refer to the wide literature available, for example, Granger and Newbold (1974), Hendry (1980), Phillips (1986) and Hendry and Juselius (2000).

Here the hypothesis of non-stationarity for all the series considered in the analysis is evaluated through the ADF unit root tests (Said and Dickey, 1984) and the KPSS stationarity test (Kwiatkowski, Phillips, Schmidt and Shin, 1992)[4]. The results, reported in table 5.2[5], do not give a clear indication in favour of one of the two hypotheses since, for some series, the two tests show opposite results. For the two prices, for instance, the two null hypotheses of unit root and of stationarity are both refused. For fuel prices and temperature, on the other hand, the hypothesis of unit root is not refused. On this point one has always to remember that results from any unit root test must be taken carefully, in particular when the alternative is a stationary but very persistent process (in this case the unit root test presents poor size and power properties). Observing the autocorrelation function in figure 5.6 this seems to be the case.

On these grounds it is rather difficult to draw general conclusion regarding the stationarity or the non-stationarity of the electricity time series analysed. Rather, unit root tests are used here to assess "whether the finite sample data used exhibits stationary or non-stationary attributes", as advocated in Harris (1995). As Cochrane (1991) argues, the important question is not weather there exists a unit root and to classify time series into the unit root category or not, but to outline the appropriate inferential procedure. On this point, there seems to be strong evidence that the differentiated series are stationary. For this reason, even if the support in favour of a unit root is not strong, in the next sections the series are considered I(1), in order to avoid the risk of spurious regression. In this sense I follow the advice of Hendry and Juselius (2000). They suggest that "even though a variable

[4]Number of lags for the ADF selected with the AIC criterion, with 5 seasonal dummies and intercept included. Number of lags for the KPSS fixed as 4*(T/100)^1/4.

[5]In this table and in all the following tables: * = 10% significance level; ** = 5% significance level; *** = 1% significance level;

is stationary, but with unit root close to unity [...] it is often a good idea act as if there are unit roots to obtain robust statistical inference".

5.2 A static economic model of electricity aggregated demand and supply

In this section an economic model describing the supply and the demand functions in wholesale electricity markets is presented. The proposed model is static, since it describes the market with theoretical equilibrium relations and does not consider any dynamic interactions among the variables involved in the system. Nevertheless, it provides a general description, grounded in economic theory, of the interactions between the variables considered in the analysis. Therefore, this is the first step to ensure that the parameters of the dynamic econometric model proposed in the next sections are based on a solid theory and therefore assume clear economic interpretations (i.e. to ensure that the model is structural, in the sense of the Cowless Commission; see Johnston 1984).

It is worth to note that the theoretical model proposed in this section is appropriate for every electricity wholesale market which is organised as an auction, i.e. for most day-ahead power markets across the world (see section 2.3). In section 5.2.1 the theoretical economic model is presented, whereas in section 5.2.2 an empirically feasible specification is derived.

5.2.1 Stylization of the supply and demand curves

In wholesale electricity markets (see section 2.3) an independent system operator (ISO) receives supply and demand bids from the market participants and sets the clearing price and quantity at the intersection of the resulting aggregate supply and demand curves, subject perhaps to some operational constraints[6]. In this section the clearing mechanism is described approximating the aggregate electricity demand and supply curves with continuous functions.

As showed in section 3.1 the aggregated demand for electricity is strongly related to the working activities of the population and to the atmospheric conditions (particularly temperature). The non-linear relationship with these variables generates the recognised multi-level (annual, weakly and daily) seasonality of electricity demand. In contrast, as illustrated in section 4.3, a crucial aspect like the demand elasticity to price is still an open question. Briefly, in empirical models describing price dynamics (see, for instance, Karakatsani and Bunn 2005a, Weron and Misiorek 2005, Mount et al. 2006) the demand curve is typically assumed as completely inelastic, and the quantity cleared on the market is included in the model as exogenous. On the contrary, in theoretical economic models, demand elasticity is almost always assumed to be different from zero and its value is crucial for the analysis. It has been used, for instance, to identify potential market inefficiencies (Borenstein et al. 1999, Growitsch and Wein 2005) or to estimate the amount of market power (Wolfram 1999, Johnsen et al. 2004). Nevertheless, assuming a plausible value for the

[6]The System Operator ultimately needs to balance demand a supply in real-time, and will generally operate some kind of a continuous balancing market after the day-ahead auction, or power exchange, has closed. In doing so, various operational plant characteristics as well as transmission constraints will have to be met. A few markets, however, include some of these system contraints in the day ahead auction price setting.

short term demand elasticity has remained an open and crucial question in these analyses. As showed by recent empirical work (Callaway and Weale, 2005) large industrial consumers can indeed respond to high wholesale prices switching to their own backup generators or temporarily shut down production

The model proposed here can be used, *inter alia*, to test hypotheses on the demand elasticity. For this reason I consider a demand function with constant elasticity. Population activities and atmospheric conditions are identified as shifters of the demand function, which can be written as:

$$Q(P, a, b, v_d) = P^{\lambda_1} \phi(a, b) v_d \ , \tag{5.1}$$

with Q = electricity quantity traded on the market, P = electricity clearing price, a = atmospheric conditions, b = behaviour of the population (working and living habits), v_d = residual random component, λ_1 price elasticity of demand and $\phi(.)$ functional form that takes into account the non-linear features that characterise the relationships between temperature, working activities and electricity demand.

In competitive[7] electricity markets the aggregated supply curve reflects the stack of increasing marginal costs offered by different power plants in order to produce electricity. The supply is affected by three sources of variability: fuel prices, plant outages and technical rationale. The *first* one reflects that the marginal plant (i.e. the plant that is setting the price in the auction market) is often a fossil-fuel burning one, particularly during the peak

[7]Even though market power can be present from the generation side, the aggregate supply curve in well-behaving, established electricity markets is typically not too far from competitive levels. Even though this feature can vary from one market to another, the main reasons are vertical integration of firms (Mansur 2003, Karakatsani and Bunn 2005a), regulatory constraints, and the threat of entry that suppliers are facing (Wolfram, 1999). In any case, the usual way to exercise market power is to alter the production patters, reducing the amount of power plants available to produce (Borenstein et al., 1999). I directly account for this effect in the model, since one of the relevant variables considered here is the available excess capacity.

periods (the only notable exception at the moment is the NordPool, which, as illustrated in section 2.3.4, is dominated by hydropower). The *second* accounts that, according to technical, or, as many studies (see, for instance, Borenstein and Bushnell 1999, Borenstein et al. 1999) seem to evidence, strategical reasons, the amount of power plants available to produce (i.e. bidding into the market) can vary considerably from day to day. As showed in section 4.1, if some power plants bids are missing the aggregate supply curve shifts upwards. This feature is not substantial when demand is low (i.e. in the baseload) but will affect price considerably in the peak. The *third* factor affecting the supply curve is connected to the technical management of power plants. Starting or varying production of electricity requires costs and time. For this reason the cost faced by a power plant in order to produce the same amount of electricity can be different. This feature explains why wholesale prices are generally higher in the hours in which production is rapidly changing. Assuming constant elasticities the aggregate supply function can be written as:

$$P(Q, p_f, c, t_r, v_s) = \beta_0 Q^{\beta_1} p_f^{\beta_2} c^{\beta_3} \eta(t_r) v_s \ , \qquad (5.2)$$

with p_f = fuel prices, c = excess capacity available on the system (margin), t_r = technical rationale, v_s random component incorrelated with v_d, β_0 constant term depending, for instance, on the set of technologies present on the market and on the competition level; β_1, β_2 and β_3 = quantity, fuel prices and excess capacity elasticities and $\eta(.)$ is a non linear function representing the effect of technical constraints on the aggregated supply.

5.2.2 The empirical specification

The previous paragraph describes the electricity market supply and demand functions from a static, theoretical point of view. In this section an empirically tractable, linear specification of the two curves is derived from equations (5.1)-(5.2). This requires some assumptions on the non-linear functions $\phi(a, b)$ and $\eta(t_r)$.

Considering electricity demand, one can observe that most of the variability in the activity of the population is regulated on seasonal cycles with daily and weekly periodicity (see the description in section 5.1 and section 3.1.1). As previously introduced, in this analysis the daily cycle is encompassed developing a separate model for each hour of the day. As illustrated in section 3.1.2 and 3.2.3 this choice is rather established in electricity quantity and price modelling. Furthermore, the weekly cycle is handled discarding the weekends and inserting a centred dummy for each remaining day of the week. Demand for electricity is also significantly lower than usual in national festivities days. I account for this effect inserting a dummy equal to one when the day is a national feast, and zero otherwise.

Among the atmospheric variables that influence electricity demand, only temperature, which is by far the most important determinant, is considered here. As showed in section 5.1, the link between electricity demand and temperature is analogous to an asymmetric "V". This relationship cannot be linearised with a second degree polynomial (which implies symmetry) but must be handled defining two different variables from the original temperature. A threshold (see figure 5.2) that corresponds to the lowest demand of electricity (i.e. the sum of electricity demand for heating and cooling purposes is minimum) is selected. Consequently, I define cold temperature (t_{cold}) all the temperature below the threshold (electricity demand is mainly for heating purposes) and hot temperature (t_{hot}) all the temperature above the threshold (demand for cooling and air conditioning needs). Hence, the functional form that describes the influence of temperature and population behaviour on electricity demand can be written as:

$$\phi(a,b) = \lambda_0(\lambda_f^{d_f} \prod_{i=1}^{5} \lambda_i^{d_i})(\lambda_t^{d_t} \exp[\lambda_c t_{\mathrm{col}\,d} + \lambda_h t_{hot}) \ , \tag{5.3}$$

where the population behaviour effect is encompassed in the first round brackets, the atmospheric conditions (temperature) effect in the second ones, and d_f is a dummy variable taking value 1 when the day is a national holiday and 0 otherwise, $d_i, i = 1, 2, \ldots, 5$ are dummy variables identifying each day of the week; t_{cold} (t_{hot}) is equal to the atmospheric temperature when temperature is lower (higher) than the threshold and set equal to 0 otherwise and d_t is a dummy variable that takes value 1 when temperature is above the threshold and 0 otherwise. All the parameters have direct economic meaning: λ_0 is the constant term (depending, for instance, on the level of market liquidity), λ_f is the variation of the constant when the day is a national feast, λ_i are daily multiplicators capturing the seasonal behaviour on the weekly cycle, λ_c and λ_h are the semi-elasticities of demand to cold and hot temperature and λ_t is the variation of the constant when temperature is hot. Substituting (5.3) in (5.1) and applying the logarithmic transformation, one obtains the following double-log specification of the demand curve:

$$\ln(Q) = \lambda_1 \ln(P) + \ln(\lambda_0) + d_f \ln(\lambda_f) + \sum_{i=1}^{5} d_i \ln(\lambda_i) + d_t \ln(\lambda_t) + \lambda_c t_{\mathrm{col}\,d} + \lambda_h t_{hot} + \ln(v_d). \tag{5.4}$$

The choice of conducting a separate analysis for each hour of the day encompasses also most of the technical rationale $\eta(t_r)$ influencing the supply function on daily basis.

In fact, the aggregate production path follows the same dynamics from day to day and the technical constraints that power plants are facing are similar among the same hours of distinct days. The weekly effect is captured inserting a centered dummy for each day of the week and the remaining influence is included in the error-term. Hence, substituting $\eta(t_r) = \prod_{i=1}^{5} \beta_i^{d_i}$ and applying the logarithmic transformation to equation (5.2) I derive the double-log representation of the supply function:

$$\ln(P) = \ln(\beta_0) + \beta_1 \ln(Q) + \beta_f \ln(p_f) + \beta_3 \ln(c) + \sum_{i=1}^{5} d_i \ln(\beta_i) + \ln(v_s). \qquad (5.5)$$

Equation (5.4) and (5.5) describe the aggregate demand and supply function submitted for a generic hour in wholesale electricity markets. Both curves are specified in a double-log form and therefore can be empirically estimated as a system of linear equations. This representation does not include any dynamic relationship between the variables involved in the system, but considers only simultaneous effects. Nevertheless, electricity markets can also be characterised by dynamic relations. For example, if the supply function shifts upwards (and hence, the clearing price increases), the reduction of the quantity cleared on the market can be instantaneous or take place with some delay, because demand can require time to adjust to the shock. On the other hand, the effect of an impulse can be completely absorbed only after many lags. A suitable short-term empirical specification cannot avoid encompassing all these aspects. Furthermore, the estimation method must take into account that, as showed in section 5.1.2, the hypothesis of stationarity for the time series considered in this analysis is not supported by empirical evidence.

In the next section the statistical methodology developed to ensure correct inference when analysing non-stationary variables is introduced, considering also the possibility of asymmetric effects. Building on these tools, in section 5.4 a dynamic version of the system (5.4)-(5.5) is specified, and a methodology is proposed for its empirical estimation.

5.3 Econometrics methodologies for non-stationary data

As showed in section 3.2., the hypothesis of stationarity may raise subtle issue of specification also in electricity prices and quantities time series modelling and, therefore, it must be carefully evaluated. In section 5.1.2 unit root and stationarity tests are implemented on the time series considered in this analysis, and it is showed how the hypothesis of stationarity is not sustained by empirical evidence. On the contrary, the first difference of all the series appear to be stationary. For this reason the variables should be considered I(1) for modelling purposes. 'Classical' statistical inference procedures assume that observed data comes from a stationary process, i.e. a process where means and variances are constant over time. A huge number of different methods have been proposed in order to test this hypothesis; they can be divided into unit root and stationarity tests (for an extensive review see Phillips and Xiao, 1998, for a review of the applications in the context of electricity market outcomes see section 3.2).

This section consists in a brief overview of the methodologies developed to estimate models on unit root variables. A complete illustration of those techniques is beyond the scope of this text, and for an extensive description I suggest to refer to the wide literature available (see, among others, the textbooks by Banerjee et al. 1993, Johansen 1996, Maddala and Kim 1998). In section 5.3.1 the problems that may arise when estimating regressions on non stationary variables are presented, in section 5.3.2 the methodologies (error-correction models and cointegration) developed to handle such situations are illustrated. Section 5.3.3 covers some of the advanced issues on cointegration that will be useful in the following parts of the analysis. In section 5.3.4 asymmetric error-correction models are presented, since asymmetric relations may play an important role in the electricity price formation process.

5.3.1 The spurious regression problem

The literature on unit root time series testing and modelling presented a tremendous growth in the recent years. However, the problems connected with regressing a non stationary variable[8] on another have been already pointed out long time ago. Yule (1926) was the first one to formalise it, calling 'nonsense correlation' the situation where extremely high correlation is found between variables for which there is no causal explanation. He found that the coefficient of correlation between two variables x_t and y_t (indicated with ρ_{xy}) is almost normally distributed when the variables are stationary, but becomes nearly uniformly distributed when the variables contain a unit root. Yule's nonsense correlation can be illustrated defining two unit root I(1) processes, for instance electricity traded quantity and clearing price:

$$\begin{aligned} \Delta y_t &= \varepsilon_t \qquad \textit{where} \quad \varepsilon_t \sim \mathrm{IN}[0, \sigma_\varepsilon] \ , \\ \Delta x_t &= v_t \qquad \textit{where} \quad v_t \sim \mathrm{IN}[0, \sigma_v] \ , \end{aligned} \tag{5.6}$$

and:

$$E[\varepsilon_t v_s] = 0 \qquad \forall t, s \ .$$

[8] For the definitions of stationary and non-stationary variable, and further issues on stationarity and unit root testing on electricity market outcomes see section 3.2.2

The model of interest is:

$$y_t = b_0 + b_1 x_t + u_t \ . \tag{5.7}$$

The estimate of b_1 with OLS wrongly postulates that u_t is an IID process independent to x_t. Under this assumption, a significance test on the parameter b_1, based on the Student's t distribution, can be written as the ratio:

$$\frac{\hat{b}_1}{s.e[\hat{b}_1]} \ , \tag{5.8}$$

where:

$$\hat{b}_1 = \left[\sum (x_t - \bar{x})^2\right]^{-1} \left[\sum (x_t - \bar{x})(y_t - \bar{y})\right] \text{, and}$$

$$s.e[\hat{b}_1] = \frac{\hat{\sigma}_u}{\sqrt{\sum (x_t - \bar{x})^2}} \ .$$

If u_t is autocorrelated, the ratio (5.8) does no longer follows a Student's t distribution. In particular, if u_t is I(1), according to the Monte Carlo experiments in Hendry and Juselius (2000), a critical value of 14.8 is needed to define a 5% rejection frequency under the null (instead of a value around 2). This large distortion occurs because, even though $\hat{b}_1$ is an unbiased estimator of b_1, the calculated standard error underestimates its true value. The main reason is that the sum of squares $\sum (x_t - \bar{x})^2$ is not an appropriate measure of the variance of x, since $\bar{x}$ (instead of x_{t-1}) is a poor 'reference line' when x_t has a stochastic trend. As illustrated, for instance, in the simulation study of Granger and Newbold (1974), not only the t-statistic, but also other classical statistical tools, such as the F-test and the

R^2, are no longer valid in presence of non stationary variables. Hendry (1980), for instance, constructed a nonsense regression using cumulative rainfall to provide a better explanation of price inflation than did the money stock in the UK. Typical features of these spurious regressions are the high R^2, the low Durbin-Watson (1951) statistic on the levels and, on the other hand, an R^2 close to zero and a DW near 2 on the first differences. A complete technical analysis of these results is presented in Phillips (1986).

In summary, there is often a problem of falsely concluding that a relationship exists between two unrelated non-stationary series. Furthermore, even though this relation is present, valid empirical inference cannot be based on the standard tools developed by the classical statistical theory (which is founded on the hypothesis of stationarity). The error-correction models and the cointegration method, developed to address this problem, are presented in the next section.

5.3.2 Error-correction models and cointegration

As showed in section 3.2.5, a process which requires to be differentiated ones to achieve stationarity is called integrated of order one, or I(1). Examples of I(1) processes are y_t and x_t as defined in equations (5.6). In general, any linear combination of these two series will also be I(1). Statistical inference on the relations between I(1) variables cannot be conducted on the levels but must be accomplished on the differentiated variables (which are I(0)). Nevertheless, the differencing operator may rule out important information which is encompassed in the series on the levels. However, there are situations in which "there are other ways to achieve stationary other than blanket differencing" (Hendry and Anderson, 1977).

This intuition is formalized in Engle and Granger (1987), building on Davidson et al. (1978) and Granger (1981). They showed that, given two or more I(1) variables, there is the possibility that, for a given scalar (or, when considering more than two variables, a vector) β, their linear combination:

$$u_t = y_t - \beta x_t \tag{5.9}$$

would be stationary. In such cases the series are called co-integrated. Hence, even though the series considered individually are non-stationary, they will nevertheless move closely together over time, according to an equilibrium relation which remains constant. Thus, the idea of co-integration mimics the economic concept of 'long run' equilibrium, to which the economic system will converge. In other words, the variables cannot diverge indefinitely from the equilibrium state but, from some point in time, they will be re-attracted towards it. The reason is that the economic relations will hold the variables 'linked together' over time. Hence, in statistical terms, the disequilibrium in the system (represented by the term u_t in (5.9)) is a stationary variable. Citing Benerjee et al. (1993): "Co-integration may be viewed as the statistical expression of the nature of such [economic] equilibrium relationships". For instance, since electricity can be obtained as a conversion of natural gas, one might expect that a relationship would hold ultimately, keeping those two commodity prices linked togheter over time.

Co-integrated variables are characterised by having an error-correction representation, that is, the relationship among the variables may be expressed in a way that combines the advantages of modelling both levels and first differences. In error-correction models, in fact, the dynamics of both short-run (changes) and long-run (levels) are modelled simultaneously. In the bivariate case, the error-correction representation can be derived from a general ADL model:

$$y_t = b_0 + b_1 y_{t-1} + b_2 x_t + b_3 x_{t-1} + \varepsilon_t \ , \tag{5.10}$$

where y_t and x_t are both I(1), x_t is weakly exogenous according to Hendry et al. (1983), and ε_t is IID and Gaussian. Equation (5.10) can be reformulated subtracting y_{t-1} from both sides and subtracting and adding $b_2 x_{t-1}$ from the right side obtaining:

$$\Delta y_t = \alpha_0 + \alpha_1 \Delta x_t - \alpha_2 [y_{t-1} - \beta_0 - \beta_1 x_{t-1}] + \varepsilon_t \ , \tag{5.11}$$

where $\alpha_1 = b_2$, $\alpha_2 = (1 - b_1)$, $\beta_1 = (b_2 + b_3)/(1 - b_1)$, and $\alpha_0 + \alpha_2 \beta_0 = b_0$. If y_t and x_t are co-integrated, all the variables that appear in equation (5.11) are stationary. In this representation the variation of y_t depends on the variation of the exogenous variable x_t and also to the disequilibrium that is present in the system at time $t - 1$, encompassed in the term $y_{t-1} - \beta_0 - \beta_1 x_{t-1}$. Thus, the value of $-\alpha_2$ provides information on the speed of adjustment of the variable y_t towards its equilibrium value $\beta_0 + \beta_1 x_t$. For instance, if previous electricity price (y_{t-1}) is too high compared to its equilibrium value ($\beta' x_{t-1}$, with x_{t-1} containg, for instance, the quantity produced and the fuel prices), then actual price will correct downwards, and vice versa. To allow this error-correction dynamic, the value of the parameter α_2 must lie between 0 (no adjustment) and 1 (perfect adjustment in one period).

Many methodologies have been proposed to estimate model (5.11) and a review of those techniques is beyond the scope of this text. Among the most popular approaches see Engle and Granger (1987), Phillips and Hansen (1990), Stock and Watson (1993), Davidson (1998), Bruggemann and Lutkepohl (2005). Nevertheless, the methodology which became the reference point in this literature, and the one applied also in the analysis in the next sections, is the approach proposed in Johansen (1988, 1991) and further developed in Johansen (1995, 1996) and Johansen and Juselius (1994).

The Johansen technique has the strong advantage of starting with an unrestricted VAR, a system in which all variables are modelled as endogenous. VAR models have been introduced by Sims (1980) as a way to estimate dynamic relationships among economic variables without imposing strong a priori restrictions. A VAR system can be written as:

$$x_t = A_1 x_{t-1} + A_2 x_{t-2} + ... + A_k x_{t-k} + \mu + \psi D_t + u_t \ , \tag{5.12}$$

with x_t (h x 1) vector of endogenous I(1) variables, D_t vector of dummy variables (for instance seasonal dummies), u_t error term distributed as IID $N(0, \Sigma)$ and $A_1, ..., A_k$ matrixes of parameters (h x h). As analogous to equations (5.10)-(5.11), one can derive the error-correction form of the system (5.12) as:

$$\Delta x_t = \Pi x_{t-1} + \Gamma_1 \Delta x_{t-1} + ... + \Gamma_{k-1} \Delta x_{t-k+1} + \mu + \psi D_t + u_t \ , \tag{5.13}$$

where $\Pi = A_1 + A_2 ... + A_k - I$ and $\Gamma_i = -(A_{i+1} + A_{i+2} ... + A_k)$. This specification contains information on both the short run (Γ_i) and the long run (Π) relations among the variables. Following Johansen (1988), the test of cointegration can be performed as a test of reduced rank on the matrix Π. In fact, one can rewrite $\Pi = \alpha\beta'$, where the vector α represents the speed of adjustment of each variable towards the equilibrium vectors β'. In this framework, the term $\beta' x_{t-1}$ embeds the disequilibrium present in the system at time $t-1$. According to the rank r of Π three situations are possible:

$r = h$: the variables modelled in the VAR system are stationary, and any linear combination of them would also be stationary. In this case there is no problem of spurious regression and one can estimate the VAR (5.12) in levels;

$r = 0$: the variables are I(1) but they are not cointegrated, hence there are no linear combination of them that are stationary. The best modelling strategy, in this case, is a VAR on the first differences;

$0 < r \leq h-1$: the variables considered individually are I(1) but there exist r linear combinations of them which are stationary. In other words there are r cointegrating vectors, which are embedded in the matrix β. In this case Π has reduced rank equal to r.

From these considerations the test for cointegration (and for the number of cointegrating vectors) can be implemented as a test on the rank of Π. Johansen (1988) proposes two tests: the trace test and max-eigenvalue value test. Both tests are likelihood ratio (LR) tests and are based on the eigenvalues of the matrix Π. As showed in Johansen (1988), the number of eigenvalues which are significantly different from zero corresponds to the number of cointegrating relationships. Hence, the null hypothesis that there are at most r cointegrating vectors becomes:

$$H_0 : \lambda_i = 0 \qquad i = r+1, ..., h \ , \tag{5.14}$$

where only the first r eigenvalues are non-zero. The trace test for the null hypothesis in (5.14) can be written as:

$$\lambda_{trace} = -2\log(Q) = -T\sum_{i=r+1}^{h}\log(i-\hat{\lambda}_i) \ ,$$

where Q = (restricted ML/unrestricted ML). The maximal-eigenvalue test uses the same principle, and it is based on the significance of the largest non-zero eigenvalue:

$$\lambda_{\max} = -T\log(1-\hat{\lambda}_{r+1}) \ .$$

This tests that there are r cointegrating vectors against the alternative that $r+1$ exist. Asymptotic critical values for both tests are reported in Johansen and Juselius (1990) and Johansen (1996). The two tests are implemented in section 5.5 to investigate the cointegration rank of the system considered in the analysis. However, it is worth mentioning that the choice of the cointegration rank cannot be based on a blind use of any testing procedure, but must consider as much information as possible, including *a priori* economic theory. On this point see, among others, Doornik et al. (1998) and Hendry and Juselius (2001).

In discussing the formulation of the dynamic model (5.13), an important question is whether an intercept or a trend should enter the short and/or the long run model. Since the variables considered in the analysis do not present a trend, only this situation is considered here[9]. In this case the constant μ is restricted to lie in the cointegration space, in fact an absence of trend in the model on the levels (5.12) translates in an absence of the constant

[9] For a complete illustration of the topic see, among others: Johansen and Juselius (1990), Johansen (1996), Hendry and Juselius (2001).

in the model on the first differences (5.13), hence $E(\Delta x_t) = 0$. The only deterministic component (except the dummies) in the model are the intercepts in the cointegrating relations, implying that some equilibrium means are different from zero. Therefore, the estimates of the parameters β and α in model (5.13) are obtained through a maximum likelihood (ML) procedure as illustrated in Johansen (1988, 1996).

The cointegration methodology raised a great interest in literature and it would be impossible to even only cite here all the relevant aspects of this topic. On the contrary, in the next sections, I will focus on three issues which are the most relevant for the analysis in section 5.4 and 5.5: weakly exogenous variables, the identification of the cointegrating relations and the asymmetric error-correction model.

5.3.3 Further issues on cointegration

This section illustrates two features of the cointegration methodology which are intitled of particular emphasis in the analysis presented in section 5.4 and 5.5: the identification of the cointegrating relations and how to test weak exogeneity and estimating error-correction models including weakly exogenous variables.

The identification problem is particularly important, since the Johansen approach only provides information regarding how many vectors span the cointegration space, but requires restrictions motivated by economic theory to obtain unique vectors. This issue is analysed in Johansen and Juselius (1994) and Johansen (1995). The restrictions are similar to Cowless Commission type restrictions (for instance, a particular variable does not appear in one equation) but apply only in the long run, getting around Sims (1980) critique regarding the use of restrictions on the short-run dynamics in simultaneous systems of equations.

In general, just identification can be achieved imposing the appropriate normalisation and $r-1$ restrictions on each cointegrating vector β_i (hence, if there is only one cointegrating vector, normalisation is sufficient for identification). These restrictions do not change the likelihood function, hence no tests are involved. When the vectors are identified, over-identifying restrictions on the parameters β_{ij} can be tested through a LR test, as showed in Johansen (1991) and Johansen and Juselius (1994).

It is worth mentioning that, even though the VAR system (5.12) is a reduced form, the identified long run relations (i.e. the cointegrating vectors) are in a structural form. On this regard Davidson (1998) defines the structural cointegrating vectors as: "simply, parameters/relations which have a direct economic interpretation", such as "supply and demand elasticities, propensity to consume or save, etc.". Hence, if the identification procedure is grounded in economic theory, the cointegrating vectors assume the meaning of long run, equilibrium relationships, with direct economic behavioural meaning. On this point see also Pesaran and Smith (1998).

The second issue regards how to test and model cointegrating relationships including weakly exogenous variables. The definition of weak exogeneity has been introduced in Engle, Hendry and Richard (1983). According to EHR a variable is weakly exogenous when it can be considered 'as given' without losing information for inferential modelling purposes. In this case, the analysis can be conducted developing a model conditioned on the weakly exogenous variables without losing relevant information for the parameter estimation. This feature is satisfied if two conditions are valid. Indicating with θ_1 the parameter of the conditional model and with θ_2 the parameter of the marginal density of z_t, z_t is weakly exogenous if and only (1) if the parameters of interest (i.e. the parameters on which inference is conducted) can be written as a function of θ_1 and (2) if θ_1 and θ_2 are variation free (there are no cross-restrictions between them). In the cointegration framework, if the interest is placed on the long run parameters β, the concept of weak exogeneity is related to the significance of the parameter α. Consider equation (5.13) in the bivariate case, with $x_t = [y_t, z_t]$. Conditioning on z_t, with number of lags $h = 1$ and no dummy variables, the system (5.13) can be re-written as:

$$\begin{aligned} \Delta y_t &= \gamma \Delta z_t + \alpha_1 \beta' x_{t-1} + \varepsilon_{1t} \ , \\ \Delta z_t &= \alpha_2 \beta' x_{t-1} + \varepsilon_{2t} \ . \end{aligned}$$

In this representation z_t is weak exogenous for β if $\alpha_2 = 0$. In that case, z_t, even though being present in the cointegrating relation, does not adjust towards the equilibrium. Hence, it marginal density contains no additional information concerning the parameter β and efficient inference can be conducted by considering only the conditional system.

There are at least two potential advantages from estimating a model having conditioned on the weakly exogenous variables (Urbain, 1995). First, if the exogenous variables exhibit all the 'problematic' data features (such as non-normality, presence of outliers, heteroskedasticity and similar) than conditioning on those variables will usually ensure that the rest of the system presents 'better' stochastic properties. Second, the number of parameters to be estimated is reduced. The test for weak exogeneity can be conducted, as illustrated in Johansen and Juselius (1990) as a LR test:

$$-2\log(Q) = T\sum_{i=1}^{r}\log\left(\frac{1-\hat{\lambda}_i^*}{1-\hat{\lambda}_i}\right) \ ,$$

with $\hat{\lambda}_i^*$ eigenvalues of the restricted model. For further discussion on testing weak exogeneity in cointegration analysis see, among others, Johansen and Juselius (1990), Johansen (1992) and Ericsson (1992).

However, it is not unfrequent the situation in which some variables can be assumed as weakly exogenous *a priori*. This is the case of atmospheric temperature in the model presentend in the next section. In such cases the model (5.12) becomes:

$$\Delta y_t = \Lambda\Delta z_t + \Pi x_{t-1} + \Gamma_1\Delta x_{t-1} + ... + \Gamma_{k-1}\Delta x_{t-k+1} + \mu + \psi D_t + u_t \ , \tag{5.15}$$

where x_t cointains both the endogenous y_t and the exogenous z_t variables. In this situation, the critical values for the cointegration test computed in Johansen and Juselius (1990) are no longer valid. This issue is analysed in Pesaran et al. (2000), where the asymptotic and the small samples (by Monte Carlo simulation) critical values for both tests are provided.

5.3.4 The asymmetric error-correction model

Asymmetric relations may play an important role in the electricity markets clearing process. For example, if electricity price becomes higher than a threshold, industrial consumer may temporarily reduce production and hence the overall electricity demand (Callaway and Weale, 2005), whereas low electricity prices are not likely to influence the production patterns to the same extent in the short term. Asymmetric price transmission in energy commodities has also been subject of considerable attention, in particular regarding the pass-trough of oil shocks into and gasoline price (see, among others, Borenstein et al.

1997, and Chen et al. 2005).

In the asymmetric error-correction model the speed of adjustment of each variable towards the equilibrium (represented by the matrix α) may vary accordingly with the sign of disequilibrium. In the extreme case, adjustment will happen only if disequilibrium is positive or negative. This class of models was presented for the first time in Granger and Lee (1989), as a generalisation of the methodology introduced in Engle and Granger (1987), and further developed in Enders and Granger (1998) and Enders and Siklos (2001). The single equation asymmetric error-correction model can be written as:

$$\Delta y_t = \mu + I_t \alpha^+ \beta' x_{t-1} + (1 - I_t)\alpha^- \beta' x_{t-1} + \sum_{i=1}^{k} \Gamma_i \Delta x_{t-i} + u_t \ , \tag{5.16}$$

with $\beta' x_{t-1}$ disequilibrium in the system at time $t-1$, α^- adjustment coefficient when disequilibrium is negative, α^+ adjustment coefficient when the disequilibrium is positive, I_t indicator variable equal to 1 when the disequilibrim is negative and 0 otherwise, k number of lags chosen ot ensure absence of autocorrelation in the residual u_t. Equation (5.16) can be generalised allowing also the effect of the lagged variables to change with the sign of the disequilibrium.

As showed in Krolzig (1997) and Saikkonen and Luukkonen (1997), the Johansen (1991, 1996) ML methodology originally developed to estimate the cointegrating relations in linear, Gaussian systems, can be implemented even when the short-term dynamics are subject to regime-switching. This result has been used to estimate the long-run, equilibrium relationships in Markow-switching vector error correction models (MS-VECM) with the standard Johansen (1996) methodology, and to estimate the regime-dependent, short-run parameters only in a second step (Krolzig et al. 2002, Clarida et al. 2003, Tillmann 2004). Following these considerations, since asymmetric responses can be viewed as a special case of the MS-VECM, in the multivariate generalisation of (5.16) one can estimate the equilibrium relationships with the Johansen methodology as illustrated in the previous sections, and estimate the short term parameters in a second step, with FIML or IV. This approach is indeed proposed to estimate the model introduced in the next section.

5.4 The dynamic econometric specification

This section is devoted to the dynamic specification of the supply and demand system developed in section 5.2. The static model (5.4)-(5.5) assumes that the variables are affected only by simultaneous interactions. Nevertheless, empirical evidence shows that dynamics play a foundamental role in determining electricity markets outcomes. As illustrated in section 5.1.2, the autocorrelation functions of the series considered in the analysis are quite persistent, and the hypothesis of stationarity is not supported by statistical evidence. For this reason the variables are modelled as I(1). Hence, the model (5.4)-(5.5) implies the presence of two cointegrating vectors and can be sensibly specified including the dynamic interactions in an error-correction form. As showed in the previous section, this specification allows to encompass both short and long run relations in the same model.

On this point it is important to emphasize that in this framework the concept of 'long run' has to be interpreted in a 'short window' context. In fact, since the analysis is based on hourly data covering approximately one year and a half of time span, one cannot assume as variable all the inputs of production. Indeed, most of the investment decisions in power markets require a time span of several years, and for this reason these must be considered as fixed in this framework. Thereafter, with 'long-run' relations I will indicate static equilibrium conditions with direct economic meaning towards which the system will converge in absence of perturbations, conditional upon all the price drivers (eg. market structure changes) that need more than the elapsed time to adapt being considered fixed. In this sense, all the factors of production that need more than the time covered by the analysis to be changed must be considered as fixed in order to correctly interpret the results. Furthermore, asymmetric responses may be present in the short-term, high-frequency, interactions among demand and supply. To evaluate this potential asymmetry in the demand price response and to encompass both short and long run relations in the same framework, I specify the following asymmetric vector-error correction model (A-VECM)[10]:

$$\begin{aligned}
\Delta p_t &= \theta_{11}\Delta q_t + \delta_{11}\Delta c_t + \delta_{12}\Delta p_f + I_{St}\alpha^{+}_{Sp}\beta_S w_{S,t-1} + (1 - I_{St})\alpha^{-}_{Sp}\beta_S w_{S,t-1} + \\
&\quad + I_{Dt}\alpha^{+}_{Dp}\beta_D w_{D,t-1} + (1 - I_{Dt})\alpha^{-}_{Dp}\beta_D w_{D,t-1} + \phi d_{j,t} + \sum_{i=1}^{p}\vartheta'_i \Delta w_{S,t-i} + u_{St}
\end{aligned} \tag{5.17}$$

$$\begin{aligned}
\Delta q_t &= \theta_{21}\Delta p_t + \delta_{21}\Delta t_{\mathrm{col}\,d} + \delta_{22}\Delta t_{hot} + I_{St}\alpha^{+}_{Sq}\beta_S w_{S,t-1} + (1 - I_{St})\alpha^{-}_{Sq}\beta_S w_{S,t-1} + \\
&\quad + I_{Dt}\alpha^{+}_{Dq}\beta_D w_{D,t-1} + (1 - I_{Dt})\alpha^{-}_{Dq}\beta_D w_{D,t-1} + \varphi d_{j,t} + \sum_{i=1}^{k}\varsigma'_i \Delta w_{D,t-i} + u_{Dt}
\end{aligned}$$

with:

p_t : logarithm of the clearing price;

q_t : logarithm of the traded quantity;

[10] Also a more general specification, embedding asymmetric effects of the lagged variables, has been considered. Its coefficients did not show any significant asymmetry and therefore only the asymmetric error-correction version is presented here.

c_t : logarithm of the available capacity;

p_f : logarithm of the fuel prices;

t_{cold} and t_{hot} : atmospheric temperature variables defined as in (5.3)[11];

d_j : vector of dummy variables containing both d_i and d_f;

$w_S = [p_t, q_t, c_t, p_f, 1]$ a vector containing only the variables embedded in the supply fuction;

$w_D = [q_{,t}\, p_t, t_{hot}, t_{cold}, d_t, 1]$ a vector containing only the variables embedded the demand function;

$I_{St}(I_{Dt})$: indicator variable for positive disquilibrium in the supply (demand) side, equal to 1 when $\beta_S w_{S,t-1} > 0$ ($\beta_D w_{D,t-1} > 0$) and to 0 otherwise;

p and k : number of lags selected to assure serial incorrelation in the Gaussian residual components u_{Dt} and u_{St}.

In this representation clearing prices and quantities traded on the market react to the short term dynamics of the supply and demand shifters and also are attracted towards the long-run equilibrium vectors through an error-correction mechanism . All the variables of the system are stationary, since they are first difference of I(1) variables or their stationary linear combination. In fact the vectors β's are such that $\beta' w_t \sim I(0)$, i.e. they are cointegrating vectors. As showed in section 5.3, from a pure statistical point of

[11]The two variables Δt_{cold} and Δt_{hot} are not simply the first differences of t_{cold} and t_{hot}. In fact, in order to linearise a relation in the first difference, one has to consider that if during the intra-period variation the temperature crosses the threshold the relationship with quantity is reverted. To overcome this problem I define as Δt_{hot} all the variation of the temperature that occurs above the threshold and as Δt_{cold} all the variation that occurs below. If, for instance, the threshold is 60^oF and temperature drops from 63^oF to 55^oF, the variable Δt_{hot} will take value -3 and the variable Δt_{cold} will be defined as -5.

view the cointegrating vectors have to be interpreted as equilibrium states: “to which the system is attracted, other things being equal” (Banerjee et al., 1993). Furthermore, if the restrictions introduced to identify them are based on economic theory, one can interpret the cointegrating relations as long-run behavioural relationships, with direct economic meaning (Johansen 1995). For this reason they have been defined as "structural" (Davidson, 1998). Model (5.17) is consistent with a cointegration rank $r = 2$, where the cointegrating vectors are identified as the electricity aggregate supply and demand function imposing the appropriate restrictions based on equations (5.4)-(5.5). The first equation in model (5.17) is a short run supply function, in which the clearing price react to the short term dynamics of the supply shifters (fuel prices and excess capacity) and also corrects towards the ‘long-run’ equilibrium supply and demand curves through an error-correction mechanism. The second equation is a short run demand function, in which the quantity traded on the markets is influenced by the demand shifters (temperature and working habits) and corrects toward the equilibrium curves with two error-correction terms. Additionally, the effects of disequilibrium in both the supply and demand side can be different if the disequilibrium is positive or negative.

Hence, all the parameters of this model have structural interpretation. The cointegrating vectors β_S and β_D cointain the long run supply and demand elasticities. The error-correction terms $\beta_S w_{t-1}$ and $\beta_D w_{t-1}$ describe the disequilibrium of the system in the period $t-1$ compared with the long run supply and demand functions. The adjustment coefficients α_{Sp}, α_{Dp} and α_{Sq}, α_{Dq} represent the speed of adjustment of the clearing quantity and price to past disequilibrium in the supply and demand functions. Finally, θ_{11} and θ_{21}

are the short run elasticities of the supply function to quantity and of the demand function to price, whereas δ_{11}, δ_{12}, δ_{21} and δ_{22} are short run elasticities and semi-elasticities and ϕ and φ embody the effects of festivities and of the weekly cycle.

When $\alpha^{+}_{Sq} \neq \alpha^{-}_{Sq}$ demand responds differently to a positive or to a negative disequilibrium in the supply side. If, on the other hand, $\alpha^{+}_{Sq} = \alpha^{-}_{Sq} = \theta_{21} = \beta_{D1} = 0$, demand is perfectly inelastic and the quantity cleared on the market does not react at all to price dynamics but is only determined by temperature and consumer behaviour. Moreover, if $\alpha^{+}_{Sq} = \alpha^{-}_{Sq} = 0$ a partial system analysis based only on the first equation in (5.17) is efficient to estimate the long run supply curve (i.e. quantity is weakly exogenous for the long run parameters). If, on the contrary, at least one between α_{Sq} and α_{Sq} is different from zero, demand is still inelastic in the short run ($\theta_{11} = 0$) and in the long run ($\beta_{D1} = 0$), but the quantity traded on the market reacts to a system price higher or lower than the equilibrium level through the error correction term. In this case a single equation framework does no longer contains all the information available on the long run parameters (i.e. quantity is no longer exogenous). Finally, if $\beta_{D1} \neq 0$, demand is still inelastic in the short run but has a significant long run elasticity (i.e. price enters in the long run demand function).

As showed in section 5.3, the equilibrium vectors β_D and β_S can be estimated starting from a general VAR model, as introduced in Johansen (1996). This choice allows the modeling approach to begin with a general specification and test successively the structural economic model as a reduction of the statistical model describing the data. This 'data based' approach is advocated, among others, in Hendry and Mizon (1993), Johansen and Juselius (1994) and Hendry (1995). Furthermore, as illustrated in section 5.3.4, this approach is still valid even though the short-run dynamics present non-linearities.

Hence, in order to estimate the cointegrating relations, I start from a reduced form VAR model considering all the variables as endogenous 'a priori' (with the exception of the temperature, which is introduced as weakly exogenous) and only in a second step I insert the non-linearities in the model. Defining $y_t' = [p_t, q_t, c_t, p_f]$, $z_t' = [t_{hot,t}, t_{cold,t}, d_{t,t}]$ and $x_t' = [y_t', z_t']$ the VAR system in which is nested model (5.17), and corresponding to the reduced form, dynamic version of equations (5.4)-(5.5) can be written as:

$$y_t = B_0 z_t + A_1 x_{t-1} + ... + A_k x_{k-1} + \mu + C d_{j,t} + u_t \ , \tag{5.18}$$

with k number of lags selected long enough to assure absence of autocorrelation in the residual component u_t, assumed to be Gaussian, uncorrelated and homoskedastic; μ vector of constant terms; $d_{j,t}$ vector of dummies defined as previously. All variables, except temperature, are expressed in their natural logarithms. If the VAR model is correctly specified, the test for cointegration can be implemented with the technique based on the reduced rank regression introduced in Johansen (1991). Since the VAR model contains exogenous regressors the asymptotic critical values presented in Johansen (1991) are no longer valid. For this reason I use the asymptotic critical values provided in Pesaran et al. (2000). For a fixed cointegration rank, the error-correction representation of equation (5.18) can be written as:

$$\Delta y_t = \varpi \Delta z_t + \alpha \beta' x_{t-1} + \Gamma_1 \Delta x_{t-1} + ... + \Gamma \Delta x_{t-k+1} + C d_{j,t} + u_t \ , \tag{5.19}$$

where the vector $\beta' s$, as in (5.17), are such that $\beta \prime x_t \sim I(0)$. As stressed in Johansen (1995) one has to impose $r - 1$ restrictions on each of the cointegrating vectors in order to identify the system. In this framework, when $r = 2$, the identifying restriction can be imposed following equations (5.4)-(5.5). This ensures that the cointegrating relations preserve a clear economic interpretation.

When the cointegrating vectors are identified as the 'long run' supply and demand functions, one can test the hypotheses of weak exogeneity of fuel prices and excess capacity simply performing a test on the adjustment coefficients (see section 5.3)[12]. If the hypotheses are not rejected, a partial system analysis involving only the demand and the supply equations is efficient to estimate the long run parameters of the two curves (i.e. the marginal distribution of capacity and fuel price does not contain any additional relevant information). Furthermore, after estimating the cointegrating vectors $\beta's$, the short term dynamics can be investigated estimating the structural model (5.17) with FIML, assuming the residual component u_{St} and u_{Dt}, normodistributed, homoskedastic and serially uncorrelated.

Synthetically, the steps involved in the empirical estimation of (5.17), following a 'data based' approach which starts with estimating a proper statistical models describing data dynamics and then derives the structural economic model can be summerised as follows:

1. estimate with OLS (equivalent to ML) the reduced form VAR (5.18) with all the variables (except temperature) included as endogenous;

2. test for the cointegration rank r using the trace and the max-eigenvalue tests;

3. if $r = 2$, identify the cointegrating vectors as the 'long run' supply and demand functions imposing the restrictions following equations (5.4)-(5.5);

[12] I assume symmetry in the response of fuel prices and excess capacity to supply disequilibrium. Since the focus of this section is on the electricity demand response, this is not likely to be a crucial weakness.

4. test the hypothesis of weak exogeneity of the excess capacity and the fuel prices;

5. if this the hypotheses of weak exogeneity are not refused re-estimate a partial VAR system where quantity and price are modeled conditional on temperature, excess capacity and fuel price and estimate the cointegrating vectors with $r = 2$.

6. estimate with FIML the error-correction model describing the short run relationships between price and quantity, keeping fixed the cointegration vectors at the values estimated at the previous step.

This procedure ensures that the error-correction model (5.17) estimated at the last step is both founded on strong statistical grounds and on economic theory. Furthermore, it provides inference which is robust against the risk of spurious regression and endogeneity of the regressors, since the estimation procedure is based on the cointegration methodology and starts with a reduced form VAR in which all the variables are modeled as endogenous. The model can be used, inter alia, to give significant insights regarding the 'elasticity dilemma' (see section 4.3) since it contains the estimates of both the short run and the 'long run' demand elasticities. In addition, it encompasses not only instantaneous relationships, but also dynamic interactions, which play a fundamental role in the electricity market price formation process. Finally, the possibility of an asymmetric response in the short-run electricity demand function is considered and embedded in the model. Given its generality, it can be applied to most wholesale markets across the world.

5.5 The empirical analysis

In this section the modelling strategy presented previously is implemented on PJM wholesale electricity market data. As introduced in section 5.1 and 5.3, the different hours of the day are modelled separately. To evaluate the modelling technique in two distinct contexts, a baseload period (hour 24) and a peak period (hour 19) are selected. The descriptive analysis for both hours is reporeted in section 5.1. As showed in section 5.1.2, since the data do not support the hypothesis of stationarity, the variables involved in the system (5.18) are assumed I(1), and therefore modelled through the cointegration methodology (Johansen 1991, Johansen and Juselius 1994 and section 5.3.2).

System (5.18) is estimated separately for both hours via OLS, with number of lags (selected with the AIC criterion) $k = 2$. In the vector $d_{j,t}$ are included also six variables to encompass the "gas price spike" represented in figure 5.5. In table 5.3 and 5.4 are reported the descriptive statistics[13] of the endogenous variables involved in the model (5.18) and the specification tests conducted on the VAR residuals.

The main problem of this specification is the strongly rejection of the normality assumption for some of the equations random components, in particular for the coal price and for the excess capacity ones. This feature, related to the step-function dynamic of the two series (see figure 5.3) cannot be modelled in a parsimonious way but would require the inclusion of many dummy variables. Since the choice of two lags leaves no sign of significative residual autocorrelation, we carry on the analysis with this model, bearing in

[13] Normality test computed as in Doornik and Hansen (1994); AR LM test computed regressing the residuals on the original variables and lagged residuals as in Doornik and Hendry (1997); Arch LM test computed regressing the squared residuals on the lagged squared residuals, as in Lütkepohl H., Krätzing M. (2004). These definitions are valid for all the section if not otherwise specified.

	P_t	q_t	c_t	p_{gas}	p_{coal}
$\bar{x}$	3.15	10.41	7.39	1.49	3.50
$\hat{s}$	0.36	0.13	0.30	0.28	0.12
x_{skew}	0.99	0.04	-0.72	0.60	-0.93
x_{kurt}	0.84	-0.91	-0.02	1.60	-0.44
$Norm\ \chi^2_{(2)}$	71.82	12.85	32.33	61.91	56.71
Residuals					
ε_{sd}	0.17	0.04	0.12	0.03	0.004
ε_{skew}	0.31	0.13	-0.26	0.05	-2.69
ε_{kurt}	4.09	4.52	23.99	3.47	39.67
Tests					
$AR\ LM$ 1-4	0.695	2.15	1.12	0.538	0.486
$F_{(4,330)}$	[0.596]	[0.07]	[0.345]	[0.701]	[0.746]
$Arch\ LM$ 1-4	2.21	1.57	0.09	1.92	0.13
$F_{(4,326)}$	[0.07]	[0.177]	[0.985]	[0.106]	[0.971]
$Normal$	16.65	35.1	919	3.76	495
$\chi^2_{(2)}$	[0.000]	[0.000]	[0.000]	[0.152]	[0.000]

Table 5.3: Hour 24 VAR descriptive statistics and diagnostic tests, series in natural logarithms

	P_t	q_t	c_t	p_{gas}	p_{coal}
$\bar{x}$	3.87	10.60	7.39	1.49	3.50
$\hat{s}$	0.44	0.15	0.30	0.28	0.12
x_{skew}	0.03	0.17	-0.72	0.60	-0.93
x_{kurt}	-0.48	-0.58	-0.02	1.60	-0.44
$Norm\ \chi^2_{(2)}$	9.20	3.66	32.33	61.91	56.71
Residuals					
ε_{sd}	0.20	0.05	0.12	0.03	0.005
ε_{skew}	-0.38	0.01	-0.24	0.013	-2.58
ε_{kurt}	4.61	4.11	23.41	3.47	41.09
Tests					
$AR\ LM$ 1-4	0.498	0.95	0.59	0.877	0.42
$F_{(4,330)}$	[0.737]	[0.433]	[0.669]	[0.477]	[0.795]
$Arch\ LM$ 1-4	1.38	2.09	0.105	1.88	0.162
$F_{(4,326)}$	[0.24]	[0.082]	[0.981]	[0.113]	[0.958]
$Normal$	27.67	24.61	881	4.23	597
$\chi^2_{(2)}$	[0.000]	[0.000]	[0.000]	[0.101]	[0.000]

Table 5.4: Hour 19 VAR descriptive statistics and diagnostic tests, series in natural logarithms

mind the non-normality drawback[14]. On this point Gonzalo (1994) showed that the finite sample properties of the Johansen (1991) cointegration methodology are consistent with the asymptotic results even though the residuals are non-Gaussian. Hence, even though strong, the non-normality of the residuals is not likely to be a crucial specification weakness. In addition, some non-normality can be expected considering the non-linearities that may characterise in the short run dynamics. Anyway, the choice of the cointegration rank cannot be based only on the cointegration tests, since the critical values for the model with exogenous regressors (Pesaran et al., 2000) are founded on the normality assumption and can be altered by the presence of dummy variables.

However, even though these critical values must be considered only as indicative, both the trace and the max-eigenvalue tests, presented in table 5.5[15], support the choice of a cointegration rank equal to 2. The magnitudes of the eigenvalues sustain this choice, since the first two appear to be significantly bigger than the others. Furthermore, two cointegrating relationships are consistent with the structural model (5.17). For these reasons, basing the choice on both statistical evidence and economic theory, I select a cointegration rank $r = 2$ and identify the cointegrating vectors with the long-run demand and supply functions imposing the suitable restrictions according to model (5.4)-(5.5). Hence, the cointegrating vectors assume structural economic meaning, as showed in Johansen and Juselius (1994) and Davidson (1998). The estimates of the cointegrating vectors and of the adjustment coefficients are reported in table 5.6 and 5.7.

[14]I compared the Johansen ML estimation results with the ones obtained through an alternative method, namely the 2SLS advocated by Davidson (1994) and Hsiao (1997). This approach relies mainly on economic 'a priori' information and requires less stringent statistical assumption. The results, available under request, are essentially the same and therefore not reported here.

[15]The critical values (5% and 10%) in table 5.5 are taken from table 6.2 in Pesaran et al. (2000), specification with 3 exogenous variables.

TRACE TEST						
H_0	r	p-r	Hour 24	Hour 19	5%	10%
	0	5	157.21***	157.06***	108.6	103.6
	1	4	76.38*	76.76*	81.25	76.69
	2	3	33.64	33.28	56.28	52.71
	3	2	16.66	16.72	35.46	32.38
	4	1	4.88	3.91	17.80	15.68
MAX-EIGENVALUE TEST						
H_0	r	p-r	Hour 24	Hour 19	5%	10%
	0	5	80.83***	80.29***	43.62	40.86
	1	4	42.74**	43.48**	37.83	35.08
	2	3	16.98	16.56	31.56	28.83
	3	2	11.78	12.81	24.97	22.54
	4	1	4.88	3.91	17.80	15.68
EIGENVALUES						
		1	2	3	4	5
Hour 24		0.1996	0.1111	0.0457	0.0319	0.0134
Hour 19		0.1984	0.1129	0.0446	0.0347	0.0107

Table 5.5: Cointegration tests and eigenvalues

The supply curves in both hours present a strong elasticity to quantity, a result which is consistent with the price formation process in wholesale markets, as illustrated in section 4.1. As expected, the supply curves in the different hours are differently affected by the two fuel prices. Coal price is an important determinant of the baseload supply curve, whilst in the peak the coefficient presents a sign that is even the opposite of the one implied by economic theory (even though insignificant). This feature is explained considering that coal is a marginal fuel only during the baseload, whereas in the peak hours marginal plants are mainly gas-fired ones. For this reason the coal coefficient is restricted to be zero in the peak hour analysis.

Comparing the loading factors one can notice that the ones of capacity, coal price and gas price seem to be quite small, particularly for the peak hour. Testing the

Hour 24				
	supply		demand	
	$\hat{\beta}$	$\chi(1)$	$\hat{\beta}$	$\chi(1)$
Price	1	–	-0.128	3.18
Quantity	-1.429	13.54***	1	–
Capacity	0.071	1.42	0	–
Coal price	-1.832	6.51**	0	–
Gas price	-0.397	22.23***	0	–
Temp. hot	0	–	-0.017	24.6***
Temp. cold	0	–	0.008	35.01***
Dummy temp.	0	–	1.507	28.77***
Constant	18.002	11.26***	-10.330	8.13**
Loading factors				
	α_{sup}	α_{dem}		$\chi(2)$
Price	-0.577	-1.410		51.43***
Quantity	-0.126	-0.464		41.36***
Capacity	0.056	0.177		1.05
Coal price	0.003	0.002		5.75
Gas price	0.005	0.095		5.5
Weak exogeneity tests				
$\alpha_{coal} = \alpha_{gas} = \alpha_{cap} = 0$	$\chi_{(6)} = 10.88$ [0.092]			

Table 5.6: Cointegrating vectors and loading factors, with LR significance tests

joint significance of those adjustment coefficients does not refuse the null hypothesis for both hours. This result implies that the three supply curve shifters are weakly exogenous (see section 5.3.2). Therefore, model (5.18) can be re-specified as a partial VAR system where hourly quantities and prices are modeled conditional on temperature, capacity and fuel prices. The system is equivalent to equation (5.15) with $y_t = [p_t, q_t]$ and $x_t = [p_{gas}, p_{coal}, c_t, t_{hot,t}, t_{cold,t}, d_t]$. The estimates of the cointegrating vectors resulting from this model are reported in table 5.8.

All the coefficients present the sign implied by economic theory. As expected, (see figure 5.2) the effect of temperature on demand changes when temperature crosses the threshold. Not only the sign is reversed, but also the magnitude of the coefficient is

Hour 19				
	supply		demand	
	$\hat{\beta}$	$\chi(1)$	$\hat{\beta}$	$\chi(1)$
Price	1	–	-0.066	0.51
Quantity	-1.777	7.96**	1	–
Capacity	0.071	0.34	0	–
Coal price	1.420	1.79	0	–
Gas price	-0.618	14.93***	0	–
Temp. hot	0	–	-0.022	12.34***
Temp. cold	0	–	0.008	20.04***
Dummy temp.	0	–	1.873	14.98***
Constant	10.565	4.17*	-10.639	9.71**
Loading factors				
	α_{sup}	α_{dem}		$\chi(2)$
Price	-0.444	-1.307		42.08***
Quantity	-0.082	-0.418		27.02***
Capacity	0.021	0.125		0.73
Coal price	0.000	-0.003		0.41
Gas price	-0.004	0.055		2.36
Weak exogeneity tests				
$\alpha_{coal} = \alpha_{gas} = \alpha_{cap} = 0$		$\chi_{(6)} = 2.97$ [0.81]		

Table 5.7: Cointegrating vectors and loading factors, with LR significance tests

different. In fact, for each degree above the threshold, electricity response is almost double than for each degree lower than the threshold (i.e., $\beta_{temp.hot} \simeq 2\beta_{temp.\,\mathrm{col}\,d}$). This feature justifies the choice of not modelling this relationship with a quadratic polynomial, which would restrict the two coefficients to be the same.

Supply elasticities in both hours are quite high, reflecting two steep supply functions. On the contrary, the two demand curve elasticities are not significantly different from zero. One can conclude that the long-run level of demand is not significantly affected by the level of price. As stressed before, in this context one has to bear in mind that a relative 'long run' is considered here. The time span on which it is estimated the model, in fact, does not allow long run investments to take place. Therefore, the effect of potential

	Hour 24				*Hour 19*			
	supply		*demand*		*suppy*		*demand*	
	$\hat{\beta}$	$\chi(1)$	$\hat{\beta}$	$\chi(1)$	$\hat{\beta}$	$\chi(1)$	$\hat{\beta}$	$\chi(1)$
Price	1	–	0.031	0.3	1	–	0.105	1.49
Quantity	-2.127	15.39***	1	–	-2.500	12.31***	1	–
Capacity	0.171	3.69*	0	–	0.231	2.71	0	–
Coal price	-3.011	7.24**	0	–	0	–	0	–
Gas price	-0.715	29.34***	0	–	-0.867	23.32***	0	–
Temp. hot	0	–	-0.017	24.98***	0	–	-0.024	17.22***
Temp. cold	0	–	0.009	42.04***	0	–	0.011	16.43***
Dummy t.	0	–	1.573	30.9***	0	–	2.119	20.93***
Constant	29.004	19.33***	-10.879	14.54***	22.372	12.7***	-11.459	12.15***

Table 5.8: Cointegrating vectors with coal, gas and capacity as weakly exogenous

investments in energy-saving machineries or in new back-up generators does not show up in this analysis. For this reason, in presence of high prices, consumers can only temporarily alter their consumption; whereas their ‘long run’ aggregated demand remains unchanged. This feature translates in an inelastic ‘long run’ demand. In other words, in equilibrium, the level of aggregated quantity does not depend on the level of price. This feature does not necessarily imply that in the short run the quantity traded on the market is not sensible to high prices.

Short run and instantaneous dynamics can be investigated estimating model (5.17) with FIML. Under the hypotheses of cointegration rank $r = 2$ and of weak exogeneity of excess capacity and fuel prices (both not refused previously) the model is the structural form of the VAR system (5.18). The cointegrating vectors β_S and β_D are the ones estimated at the previous step, and therefore kept fixed to the values reported in table 5.8. Following a “general to specific” approach (Hendry and Mizon 1993, Hendry 1995) I eliminate the non-significant coefficients (threshold: $|t\_stat| < 1.5$), obtaining the final model estimates

Variable	*Quantity* *Coefficient*	*t-stat.*	*Variable*	*Price* *Coefficient*	*t-stat.*
EC sup(+)	-0.085	-5.83	EC supply	-0.196	-5.48
EC dem(+)	-0.210	-3.25	Δc_t	-0.134	-2.02
EC dem(-)	-0.485	-8,74	Δq_t	3.43	12.6
$\Delta t_{hot,t}$	0.014	13.2			
$\Delta t_{\mathrm{col}\,d,t}$	-0.0043	-6.60	$\Delta p_{gas,t-1}$	0.677	4.96
Δq_{t-1}	-0.076	-1.52	Δp_{t-1}	-0.072	-1.85
$\Delta t_{hot,t}$	-0.0022	-2.14			
$\Delta t_{\mathrm{col}\,d,t}$	0.0013	2.16	$d_{f,t}$	0.129	2.09
$d_{f,t}$	-0.064	-4.25	$d_{1,t}$	0.001	0.02
$d_{1,t}$	-0.016	-2.141	$d_{2,t}$	0.025	0.86
$d_{2,t}$	-0.034	-4.79	$d_{3,t}$	0.079	2.65
$d_{3,t}$	-0.031	-4.48	$d_{4,t}$	0.081	2.61
$d_{4,t}$	-0.046	-6.62			
$\sigma_u = 0.0427$		$\varepsilon_{skew} = \ 0.19$	$\sigma_u = 0.169$		$\varepsilon_{skew} = -0.23$
$R^2 = 0.45$		$\varepsilon_{kurt} = \ 4.6$	$R^2 = 0.51$		$\varepsilon_{kurt} = 3.2$
Arch 1-4 (LM): F(4,353) = 1.70 [0.150]			Arch 1-4 (LM): F(4,353) = 3.51 [0.008]		
Test for vector-autocorrelation: F(16,696) = 1.36 [0.155]					
Test of vector-arch (LM test) Chi (36) = 84.24 [0.000]					
Test for over-identifying restrictions, Chi (19) = 18.77 [0.471]					

Table 5.9: Simultaneous equations estimates and specification tests, hour 24

reported in table 5.9-5.10. The over-identifying restrictions are not rejected according to the likelihood ratio, Chi-squared test (with p-values 0.47 and 0.70). The models appear to be well specified in both hours, even though the residuals are still non-normal. Nevertheless, the model fitting seems to be quite satisfactory for both hours, as showed in figure 5.7 and 5.8. Observing the plots, the model seems to be able to capture the few spikes present in the series, with perhaps the exception of the firsts two in the hour 19 prices. Except for those two cases (which, in fact, present the highest values for the standardized residuals), the residuals look quite small and well-behaving. The R^2s are particularly high, considering that I am modelling first differenced series characterised by elevated variability.

	Quantity			*Price*	
Variable	*Coefficient*	*t-stat.*	*Variable*	*Coefficient*	*t-stat.*
EC sup (+)	-0.037	-2.83	EC supply	-0.165	-4.97
EC dem	-0.266	-7.92	Δc_t	-0.114	-1.65
$\Delta t_{hot,t}$	0.0197	15.1	Δq_t	3.70	17.8
$\Delta t_{\mathrm{col}\,d,t}$	-0.0042	-5.46	Δq_{t-1}	0.86	4.06
Δq_{t-1}	-0.267	4.40	$\Delta p_{gas,t-1}$	0.304	2.19
Δp_{t-1}	0.034	2.17	Δp_{t-1}	-0.230	-4.18
$d_{f,t}$	-0.106	-6.23			
$d_{1,t}$	-0.013	-1.55	$d_{1,t}$	-0.094	-3.03
$d_{2,t}$	-0.027	-3.17	$d_{2,t}$	-0.121	-4.07
$d_{3,t}$	-0.027	-3.27	$d_{3,t}$	-0.056	-1.87
$d_{4,t}$	-0.048	-5.61	$d_{4,t}$	-0.092	-2.94
$\sigma_u = 0.0507$		$\varepsilon_{skew} = 0.11$	$\sigma_u = 0.173$		$\varepsilon_{skew} = -0.33$
$R^2 = 0.49$		$\varepsilon_{kurt} = 4.2$	$R^2 = 0.67$		$\varepsilon_{kurt} = 4.4$
Arch 1-4: F(4,354) = 1.74 [0.139]			Arch 1-4: F(4,354) = 0.91 [0.458]		
Test for vector-autocorrelation: F(16,698) = 1.47 [0.104]					
Test of vector-arch (LM test), lags 1-4: Chi (36) = 40.47 [0.279]					
Test for over-identifying restrictions, Chi (21) = 17.20 [0.700]					

Table 5.10: Simultaneous equations estimates and specification tests, hour 19

Observing the coefficients, the first interesting feature is that there is no mutual, simultaneous influence between price and quantity. In fact the price variation coefficient is insignificant in the quantity equation for both hours and therefore dropped from the model. On the other hand the instantaneous elasticity of supply to quantity is quite substantial: it is, in fact, 50% higher than the long run estimate. Hence, at an instantaneous level, a sudden supply shift (for instance, an unplanned plant outage) reflects in an abrupt change in price and is not smoothed by a reduction of the traded quantity. Moreover, since both the short and the long run elasticities of demand are not significantly different from zero, the demand curve can be considered as perfectly vertical. However, this feature does not imply that the quantity traded on the market is not price-responsive, since it significantly reacts to past disequilibrium in the long run supply function through the error-correction term. Furthermore, the demand response to disequilibrium on the supply side is asymmetric: when supply disequilibrium is negative there is no significant short-term reaction in demand (the α^{-}_{Sq} coefficients were not significant and therefore dropped from the models), whereas when price is higher than in the equilibrium, demand shows a significant reduction. Hence the demand function, even though vertical, does adjust to past high prices shifting to the left according to the adjustment coefficients (-0.085 and -0.037, for base and peak respectively) relative to the long run supply function disequilibrium.

This behaviour is consistent with the empirical findings in Callaway and Weale (2005), where it is showed that industrial consumers can temporarily reduce their demand for electricity (shutting down production or using their own back-up generators) when prices are perceived as too high. According to this analysis, the response does not take place instantaneously but only after one period. On the other hand, low prices do not alter the short-run production patterns. Consequently, to correctly analyse short run electricity demand response to price, asymmetries play a fundamental role and cannot be ignored. Interestingly demand reaction is faster for the baseload hour than for the peak. It may well be that the demand side has a better perception of where the supply function "equilibrium" ("focal point") should be at baseload and/or that a greater proportion of the baseload is industrial with its higher characteristic price-responsiveness.

On the other hand, in the two supply equations there is no significant asymmetry; therefore the adjustment coefficients for positive and negative disequilibrium were restricted

Figure 5.7: Actual and fidded values, and standardized residuals, in hour 24.

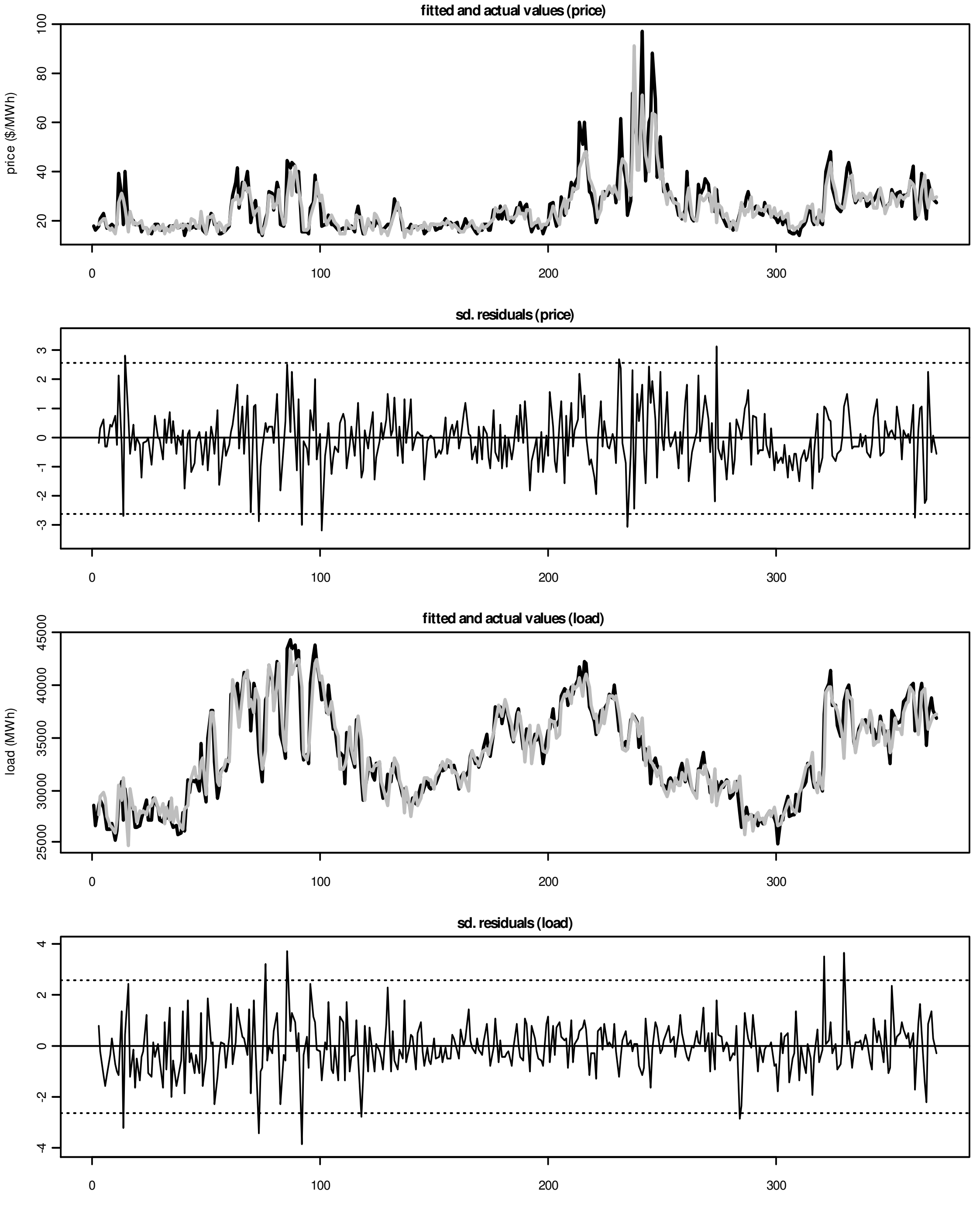
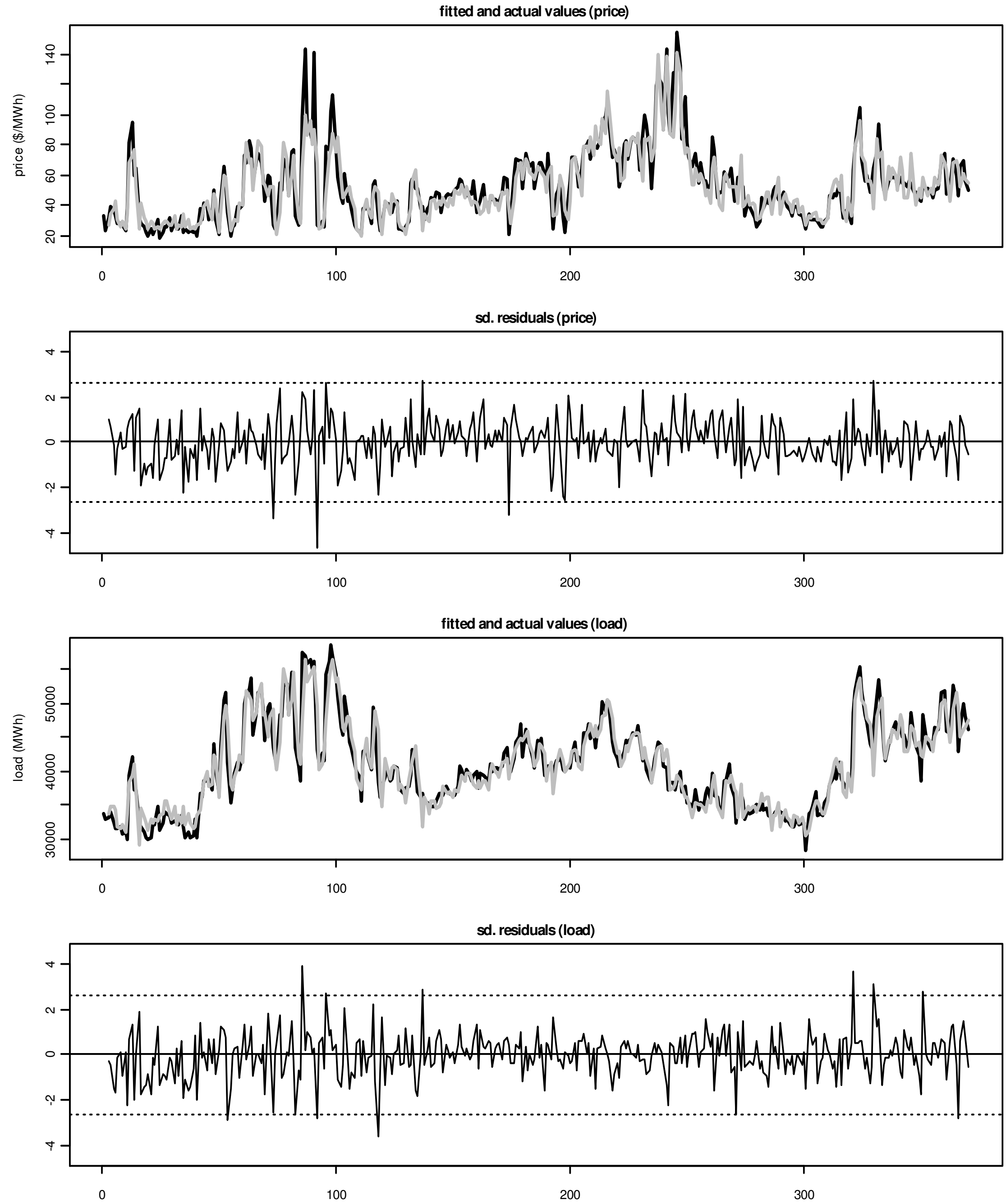


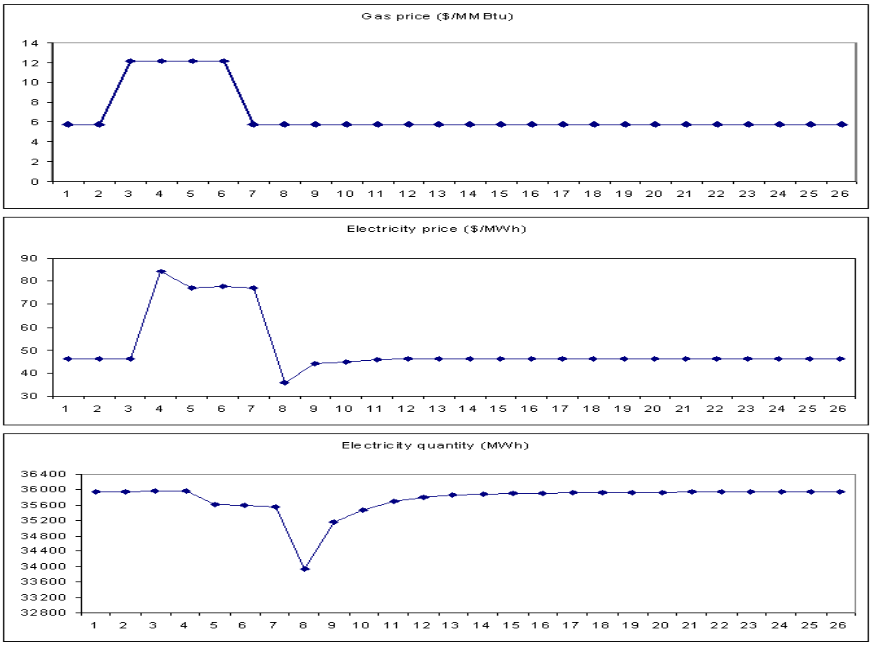
Figure 5.8: Actual and fitted values, and standardized residuals, in hour 19.



to be equal. Moreover, there is no reaction to demand disequilibrium, i.e. quantity effects the supply curves simply through the long-run and the short-run elasticities. Interestingly, in the short run the supply curve is affected by the lagged gas price and not by the current gas price. This feature may be due to a lack of synchronisation between the two markets: PJM receives bids for the day-ahead market until 12.00 a.m. of the previous day, whereas the Henry Hub day-ahead gas price closing time is at 1.00 p.m. Finally, festivity day dummies are significant in both hours, showing that during holidays there is a consistent reduction in electricity demand, both for baseload and peak.

As a final illustration, I use the model to simulate the reaction of the market to a shock on the gas price, similar to the one which took place in February 2003. I keep fixed all the other determinants (capacity, temperature and coal price) and start from a situation of equilibrium in both the supply and the demand side. Then, I assume that the gas price moves from 5.75 $/MMBtu to 12.2 $/MMBtu for 4 days to then goes back to its initial level. The dynamic response of price and quantity are showed in figure 5.7. At the beginning electricity price is lower than the level implied by the 'long run' supply function and it gradually increases adjusting towards the equilibrium. Quantity is not affected because, as long as price is lower than the equilibrium, industrial consumers do not have incentives to change their short-run production patterns. When gas price decreases again the electricity price is, for one day, higher than the equilibrium. Hence, demand is temporarily reduced. In the 'long run' (which, in this framework, is a matter of a few days) both quantity and price return to their previous equilibrium levels.

Figure 5.9: Simulated effect of a gas price shock on electricity traded quantity and price in hour 24



5.6 Conclusions

In this chapter a dynamic, structural econometric model that allows the identification and estimation of the supply and demand curves in electricity markets has been illustrated and estimated on high frequency wholesale data. The approach proposed diverges from the empirical dynamic models in the literature (see, for instance, Huisman and Mahieu 2003, Karakatsani and Bunn, 2005a, 2005b, and section 3.3.6). In fact, instead of focusing only on price dynamics in a single equation framework, it considers price and quantity interactions in a simultaneous system of equations. The identification procedure is based on a theoretical economic model which describes supply and demand function in electricity wholesale markets and, consequently, can be applied to the majority of the power markets across the world. Therefore, the model is constructed to be estimated on high-frequency (hourly) wholesale market data, which are public available in most of the countries in which the electricity sector has been liberalised. Furthermore, the estimation method is robust against the risk of spurious regression, since it is based on the cointegration methodology introduced in Johansen (1991).

The model is founded on strong theoretical grounds and provides valid inference regarding the parameters of the electricity supply and demand curves. In the empirical application (on PJM market data), it is showed that an inelastic demand does not imply that the quantity traded on the market is exogenous for the parameters of the long-run supply function. Even when demand is completely inelastic to price, in fact, the quantity traded on the market responds to past disequilibrium in the supply function. This effect is significant and asymmetric, since demand reacts if price is higher than the equilibrium but does not show any significant feedback if price is lower.

The *first* implication of this analysis is that the quantity cleared on the market can be assumed as exogenous only if the interest is focused on its instantaneous influence on price. It has been proven how this effect may significantly improve price forecasting (see, among others, Conejo et al. 2005, Weron and Misiorek 2005) in a single equation framework, but it remains an open question whether those predictions can be improved even more by including quantity as endogenous. This seems to be the case in our framework, where demand is influenced by positive disequilibrium on the supply side. On this point, lagged prices have been already used to improve quantity forecasts (Chen et al., 2001).

The *second* implication is that, if the interest is on the structural relations that characterise the supply side (i.e. the equilibrium supply function parameters) quantity needs to be modelled as endogenous, at least in the market considered here. In those analyses I observed through a unit root testing that more emphasis should be placed on the non-stationarity issue, in order to restrict potential problems of spurious regression over the time spans considered. *Thirdly*, the model shows how the reaction of consumers to high prices can take place not only instantaneously (as considered, for instance, in Borenstein et al. 2002b, Johnsen et al. 2004) but also after some delay. This feature assumes particular relevance considering that demand side responsiveness to high prices has been proposed as an effective way to mitigate market power (see Borenstein and Bushnell 1999, Borenstein et al. 2002b, Borenstein 2004 and section 4.2). In this analysis, considering inter-temporal effects (in particular the error-correction terms) would appear to be fundamental in order to correctly determine the price-demand dynamic in the daily wholesale electricity market.

Fourth, the model gives also valuable insights for the developers of theoretical models in a static framework. Particular attention in those cases has to be imposed on the time horizon for which the model is designed and accordingly choose an appropriate value of elasticity. In long-run models it seems sensible to approximate the dynamic effect of price on quantity imposing a (small) significant elasticity in the static demand curve.

Fifth, significant differences have been identified between the baseload and the peak hour. As expected, different marginal fuels characterise the two hours, but also the effect of the available excess capacity and the semi-elasticity to temperature of demand are diverse. These results bring additional support to the modelling philosophy entailing the estimation of separate models for each hour of the day.

Sixth, it is worth mentioning that the application of cointegration techniques to high-frequency data is not frequent in the literature. Examples are Baille and Bollerslev (1989) and Diebold et al. (1994). This analysis shows the potential advantages of this method in the context of electricity market.

Aspects of further development are not absent. In particular, since the model analyses separately each hour of the day, it does not embed the possibility of intra-daily effects among different hourly prices and quantities. This aspect is not likely to be substantial in many wholesale markets (like PJM or Italy), where electricity quantities for all the hours of the following day are traded in contemporaneous auctions, but deserves careful examination. In particular, it may be significant in markets where electricity is traded each period at a time, like in UK or Ontario (see section 2.3). The results in this analysis suggest that a panel cointegrating approach can potentially give important insights on this issue.

Chapter 6

Conclusions

Liberalisation has been interesting the power sector for almost two decades. Nevertheless, in competitive electricity markets, price formation and dynamics are only partially understood. In particular the non-storability of electricity, episodes of market power abuse and constraints of the market design create a peculiar environment which ultimately generates a dynamic behaviour which differs completely from those of other commodities.

Although research on electricity markets is diverse and extensive, it has mainly focused on (1) the idiosyncratic statistical properties of price and quantity (chapter 3) and on (2) general equilibrium properties used, under certain assumption of agent's behaviour and market structure, to evaluate market efficiency and in particular the potential market power from the supply side (chapter 4.2). However, few attempts have been made to test those assumptions on high-frequency, real market data, and crucial issues like the elasticity of the aggregated demand are still unresolved (chapter 4.3). On the other hand, existing dynamic models for day-ahead electricity prices present some limitation: (i) they are primarily constrained to autoregressive effects, seasonal and climate factors which, although important, are insufficient to explain price formation, (ii) they lack of economic interpretability and are, in general, reduced form equations in which quantity and margin are assumed exogenous *a priori*.

To address open research issues on price formation in day-ahead, wholesale electricity markets, this thesis defines an original econometric methodology which combines statistical accuracy with economic interpretability. This approach provides valid empirical inference on the supply and demand curves in high-frequency (hourly) day-ahead electricity markets. Through a detailed specification of the response of demand to price, the model is used (chapter 5) to give important insights on the debated demand elasticity issue, directly estimating this parameter on wholesale market data.

In terms of methodology, this approach enlightens the benefits of extending a modelling strategy historically implemented in a macroeconomic framework to micro-economic, high-frequency data. The first step is, in fact, a reduced-form VAR, in which all the variables (quantity, price, fuel prices and excess capacity) are jointly modelled as endogenous. Therefore, after rejecting the stationarity of the time series considered, the variables are tested for co-integration and, through an in-depth testing procedure, the structural model is derived as a parsimonious reduction of the statistical model describing the data. This data-based, general to specific approach is advocated, among others, in Hendry and Mizon (1993), Johansen and Juselius (1994) and Hendry (1995).

The final model is an asymmetric, structural, vector error-correction model (A-VECM) which directly estimates on day-ahead, hourly wholesale market data the aggregated demand and supply curves, distinguishing between short and long-run. Consequently, the model can be used to simulate the dynamic effects of a variation of the underlying production costs (for instance, fuel prices) on the electricity traded quantity and price. From a modelling specification perspective this reveals that the traded quantity cannot be considered as exogenous (neither weakly, nor strongly) *a priori* even for the short-run parameters. On the contrary, this assumption must be carefully evaluated since it may lead to inefficient parameter estimation and sub-optimal forecasting performances. In the empirical application on PJM market data (chapter 5.5), in fact, it is showed that an inelastic demand does not imply that the quantity traded on the market is exogenous for the parameters of the long-run supply function.

From an quantitative economic viewpoint, this thesis shows how the response of electricity demand to price can take place through a complex mechanism that can be hardly summarised using only one elasticity parameter. In this analysis I identify three different ways in which demand may react to a supply shock: instantaneously, in terms of an econometrically estimated equilibrium and through an error-correction mechanism. Even though instantaneously demand is essentially inelastic to price, the quantity traded on the market does responds to past disequilibrium in the supply function (i.e. to prices different from their "equilibrium values") through an error-correction mechanism. This effect is significant and asymmetric, since demand reacts if price is higher than the equilibrium but do not show any significant feedback if price is lower. This behaviour is consistent with the empirical findings in Callaway and Weale (2005), where it is showed that industrial consumers can temporarily reduce their demand for electricity (shutting down production or using their own back-up generators) when prices are perceived as too high. Furthermore, it is showed how different hours of the day are characterised by substantial heterogeneity. This reflects the variation of demand characteristics, and particularly the differences in the marginal plant fuels, which is mainly coal in the baseload and almost always natural gas during the peak. Without imposing any *a priori*, this intuition is reflected in the model estimates.

Overall, this thesis suggests that a comprehensive econometric model, specified at high-frequency level, can represent adequately the complexities and subtleties of the price formation process in wholesale electricity markets, achieving both an adequate statistical representation of the idiosyncratic price dynamics and a structural, economic interpretability.

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