Essays on the Evolving European Natural Gas Markets

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Contents

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p. 45, Graph from International Gas Union

List of Abbreviations

ACER	Agency for the Cooperation of Energy Regulators
ACQ	Annual Contract Quantity
ADCC	Asymmetric Dynamic Conditional Correlation (Cappiello et al., 2006)
ADF	Augmented Dickey and Fuller (Dickey and Fuller, 1979, 1981) unit root test
AR	Autoregressive
ARCH	Autoregressive Conditional Heteroscedasticity (Engle, 1982)
AVTP	Austria Virtual Trading Point, Austrian natural gas hub
BEKK	Baba, Engle, Kraft and Kroner (Engle and Kroner, 1995) specification of multivariate GARCH models
CEER	Council of European Energy Regulators
CIF ARA	Cost, Insurance and Freight Amsterdam, Rotterdam, Antwerp, coal price
CPF	Carbon Price Floor
DCC	Dynamic Conditional Correlation (Engle, 2002) specification of multivariate GARCH models
DCQ	Daily Contract Quantity
EC	European Commission
EGARCH	Exponential GARCH (Nelson, 1991)
EGARCH-X	Augmented Exponential GARCH (Lee, 1994)
EHS	Effective Half Spread

ELW	Exact Local Whittle fractional integration test (Shimotsu and Phillips, 2005)
EM	Expectation-Maximisation algorithm
EMIR	European Market Infrastructure Regulation
Eq.	Equation
ETS	Emission Trading Scheme
EU	European Union
EUA	EU (Emission) Allowances, EU carbon credit (or pollution permit) price
FELW	Feasible Exact Local Whittle fractional integration test (Shimotsu and Phillips, 2006; Shimotsu, 2010)
FTSE100	Financial Times Stock Exchange 100 Index
GARCH	Generalised Autoregressive Conditional Heteroscedasticity (Bollerslev, 1986)
GB	Great Britain
GMT	Greenwich Mean Time
GTM	Gas Target Model
ICE	Intercontinental Exchange
KPSS	Kwiatkowski et al. (1992) stationarity test
LNG	Liquefied Natural Gas
LOP	Law of One Price
MAD	Market Abuse Directive
MAR	Market Abuse Regulation
MiFID	Markets in Financial Instruments Directive
MWh	Megawatt hour
NBP	National Balancing Point, British natural gas hub
NCG	NetConnect Germany, German natural gas hub
No.	Number

NRA	National Regulatory Authority
NYMEX	New York Mercantile Exchange
OTC	Over-the-Counter
PEG	*Point d' échange de gaz*, French natural gas hub
PI	Price Impact
PLR	Pseudo-Likelihood Ratio type test
PP	Phillips and Perron (1988) unit root test
PSV	Punto di Scambio Virtuale, Italian natural gas hub
QML	Quasi-Maximum Likelihood
REMIT	Regulation on Energy Markets Integrity and Transparency
RHS	Realised Half Spread
SIC	Schwarz Information criterion
ToP	Take-or-Pay
TPA	Third Party Access
TSO	Transport System Operator
TTF	Title Transfer Facility, Dutch natural gas hub
UK	United Kingdom
US	United States
VAR	Vector Autoregressive
VECM	Vector error Correction Model
VMA	Vector Moving Average
VTP	Virtual Trading Point

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Declaration

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Abstract

In this dissertation, liquidity, price volatility and integration are investigated in European natural gas markets. Liquidity in the one-month-ahead forward market is examined using tick-by-tick data and measures from financial markets. A time-varying multivariate approach is adopted to assess correlations between trading activity, volatility and liquidity. Results support the extension of the financial market microstructure theory to physical markets and contribute towards understanding dynamics and driving forces of liquidity in energy markets. They confirm that order flow affects asset prices and that a correlation exists between price volatility and liquidity. The main drivers of natural gas price volatility are identified using BEKK models, which are particularly suitable because they allow for volatility spillovers within markets. Asymmetries and changes in the fundamental drivers of demand, supply and inventory are considered, and expectations of the theory of storage are assessed. Results support fundamental values as main drivers of price volatility in natural gas markets and indicate greater integration between natural gas and electricity markets. Finally, the process towards the integration of European natural gas markets is investigated in the one-month-ahead and day-ahead forward markets. Cointegration procedures are adopted, which are robust to outliers, seasonalities, leptokurtosis and GARCH effects in the energy price time series. Results show that barriers to trade remain, which prevent full integration, mostly in day-ahead markets, and may impact competitiveness. Long-run relationships between crude oil and natural gas prices are also investigated and are not supported by data, thus highlighting increased reliance of hub pricing mechanisms to the fundamental drivers. In all, there are indications of greater exposure of hub prices to short-term dynamics in the natural gas and power sectors, which are affected by capacity allocation management and have implications for the overall efficiency of European energy sector.

Introduction

The liberalisation of European natural gas markets was part of the European political agenda in the 1990s and 2000s and has brought a deep restructuring of the natural gas industry in most European countries. The natural gas sector has moved from a monopolistic to a more competitive and fragmented environment, with different market players, some of which cover tiny shares of the traded gas volume. The development of gas markets has increased hub trading and gas-on-gas competition, thus progressively shifting natural gas pricing mechanisms from oil-indexation towards greater hub-indexation. Nonetheless, competition and higher exposure to the fundamental values of demand and supply create a need for instruments to hedge and manage risk (Pilipovic, 2007). With gas-on-gas competition and spot markets, price signals are crucial for investment decisions in the natural gas and power sectors. Market participants and policy-makers have therefore expressed concerns about the overall efficiency of wholesale European energy markets and their benefit for consumers (European Commission, 2014).

The main aim of this dissertation is to assess the current stage of the liberalisation process, by investigating indicators and drivers of market quality at the UK's National Balancing Point (NBP) and the integration of energy markets, and drawing implications for the efficiency and competitiveness of European natural gas markets. The context and literature are reviewed and three empirical studies are carried out, where theories from financial and commodity markets are used to develop measures and econometric models in order to assess liquidity, drivers of uncertainty and paths towards the single European energy market.

Chapter 1 provides the background of the research. The development of the European natural gas markets following the liberalisation process is described. Implications of liberalisation are outlined, some of which have posed new risks for market players and may affect the objectives of competitiveness and efficiency pursued by policy-makers. These potential risks, their implications and questions concerning financial investments and regulation in energy markets motivate the empirical studies that follow.

In Chapter 2, since liquidity can be regarded as a barometer of market quality, its measurement and dynamics in the forward market for natural gas are assessed, by adopting the financial perspective on market microstructure. In contrast to previous literature, a time-varying multivariate approach is used to investigate the different dimensions of liquidity. Tick-by-tick data on indicative quotes, transaction prices and volumes of one-month-ahead NBP forward contracts from a major inter-dealer broker are explored at different intervals and highlight common patterns and seasonality. After extracting these predictable components from the time series, similarities between natural gas and financial markets are found, and thus the effectiveness of measures that were designed and applied in financial markets is validated in a natural gas market. In addition, direct links between liquidity, trading activity and price volatility are examined in order to ascertain how trading affects the quality of natural gas markets. Finally, given that greater market transparency may increase transaction costs and thus decrease liquidity, whether there were changes in the dynamics and predictors of liquidity following the Regulation on wholesale Energy Market Integrity and Transparency (REMIT) is investigated via an event analysis. In all, this chapter contributes to theory and modelling in natural gas markets by extending measures and theory from the financial literature, and has implications for industry and policy makers as inferences on market quality and potential risks are made.

After having established a link between market quality and price volatility, in Chapter 3, the main drivers of price volatility in the United Kingdom natural gas spot market are addressed. Using a multivariate GARCH framework, volatility spillover effects between natural gas and other energy markets are investigated, allowing for the impact of changes in the fundamental values of demand, supply and inventory. By focusing on expectations based on the theory of storage concerning the dynamics and drivers of the spot-futures prices spread, the correlation between volatility and the fundamental values of demand, supply and inventory is highlighted. In addition, there is evidence of increasing integration between natural gas and electricity markets in the UK. On the whole, this chapter contributes to the existing literature on energy markets by illustrating the impact of market conditions in explaining uncertainty and driving co-movements in the European energy markets. The implications for market participants, policy-makers and researchers are also highlighted, as inferences are made on the changing risks and other factors affecting European energy markets stability and competitiveness.

In Chapter 4, following the observed indications of co-movements of energy markets in Europe, the focus is on the European energy market integration and the evolving relationship between natural gas and Brent crude oil markets, which followed from the liberalisation process. A robust multivariate long-run time-varying approach is used to explore changes that may have occurred in the relationships across markets. This chosen approach accounts characteristics of energy price time series that can affect market co-movements, but have been mostly neglected in previous assessments of market integration. In all, this chapter contributes to the existing literature on energy market integration by ascertaining the degree of price convergence in one-month-ahead and day-ahead European natural gas forward markets. The role of physical interconnection and financial trading in driving price convergence is highlighted, as entailed by the different degree of integration across markets and countries. Thus, factors that may foster or prevent integration in the European energy markets are inferred, and their implications for policy-makers and the energy sector are highlighted.

Finally, Chapter 5 summarises and concludes this dissertation, by reflecting on its findings and implications for future research.

1

The Development of the European Natural Gas Markets

1.1 Introduction

In the late 1980s, the European Union (EU) undertook a process of liberalisation of the energy sector with the intent to make it more competitive, and to promote the development of a single European energy market. This process was a response to the increasing concerns about the efficiency of the European energy sector in globalising markets. Since economic theory predicts that more competition leads to lower prices and greater output (Baumol et al., 1982), the liberalisation of vertically integrated and bounded energy sectors was devoted to the benefit of consumers and higher social welfare.

Greater competition in the natural gas markets was designed to improve gas-on-gas competition, with prices determined by the interaction of demand and supply. Trading based on non-discriminatory rules and market transparency was thus encouraged, with the aim to curb price volatility and to improve supply security in flexible and more integrated energy markets.

This chapter offers an overview of the process towards the liberalisation of European natural gas markets and its implications. Section 1.2 presents the EU legislative framework underlying the opening of markets to competition and the creation of a single European natural gas market. In Section 1.3, the development of physical and financial trading at European natural gas hubs is outlined. The Regulation on Energy Markets Integrity and Transparency (REMIT), which supervises natural gas trading activity, is reviewed and European financial market regulations that affect, in some forms, natural gas trading are summarised. The main features of the natural gas prices and their evolution in the European markets are discussed in Section 1.4. Section 1.5 concludes the chapter and summarises the context that motivates this research.

1.2 The Liberalisation of the European Natural Gas Markets

1.2.1 Gas directives and regulations

During the 1990s and 2000s, the establishment of a new legislative framework has deeply changed the architecture of European natural gas markets with the goal of guaranteeing EU's consumers with a real competitive choice and promoting supply security and sustainable development. The First Gas Directive (98/30/EC), adopted in May 1998, set out the preliminary steps towards competition by changing network access conditions, and by introducing legal unbundling (i.e. separate subsidiary companies for transmission and supply) and negotiated and regulated third party access (TPA). The Second Gas Directive (2003/55/EC), adopted in June 2003, replaced the First Gas Directive and, in the attempt to accelerate the process of liberalisation, it introduced liberalised access in the wholesale market by 2004 and in the retail market by 2007. This directive required management unbundling and TPA to be implemented for transmission and distribution networks (including interconnectors), liquefied natural gas (LNG) import facilities, and gas and LNG storage facilities. Furthermore, it called for the implementation of the regulation to be carried out by an independent authority. The Gas Regulation (EC) No. 1775/2005 of September 2005 established the guidelines for TPA, capacity allocation mechanisms, congestion management procedures and transparency requirements.

With the Third Energy Package, the final legislative step adopted in July 2009, the Third Gas Directive (2009/73/EC) and the Gas Regulation (EC) No. 715/2009 were introduced. The intent was to complete the opening of European gas markets to competition, by accelerating the separation of production and supply activities from transmission activities, and the non-discriminatory access to infrastructure. This was done either through ownership unbundling or through subsidiaries operating independently from the supply and trading activity branches, with a strict regulatory monitoring (independent system operators or independent transmission operators). The Third Energy Package established the Agency for the Cooperation of Energy Regulators (ACER), the European energy regulatory authority, and the European Network of Transmission System Operators for Gas (ENTSOG), with the purpose to encourage the completion of the single EU energy market.

Embedded in the Third Energy Package was the vision of a single European market for natural gas and the creation of hubs at which all gas was intended to flow for the purpose of pricing, either under long-term contracts or spot trading. Furthermore, it enhanced cross-border trade and investment and promoted regional cooperation mechanisms among European Union (EU) countries to guarantee security of supply. Mechanisms for the access to transmission system networks were introduced through the European Gas Target Model (ACER, 2015a), which are outlined in the following subsection. Overall, the evolving regulation has entailed changes in the European natural gas market conditions, which will be picked up later in the empirical studies.

1.2.2 Gas target model

Prompted by the 18^{th} Madrid Forum in 2011, the Council of European Energy Regulators (CEER) proposed a hub trading framework, namely the European Gas Target Model (GTM), which was endorsed by the 21^{st} Madrid Forum in March 2012 to foster gas-on-gas competition and share its benefits across the Member States. The GTM, and its renewed and updated version, the GTM II developed in 2014, aimed at stimulating the development of gas hubs and the integration of the EU gas markets. The model encouraged a self-assessment by the National Regulatory Authorities (NRAs) of the functioning of the national markets. Furthermore, this model recommended measures to overcome situations where the national sectors were not favourable to competition and market liquidity. Specifically, the model assumed a competitive and integrated internal gas market system, with entry/exit zones and liquid trading hubs in them. The EU Network Codes and Guidelines, underlying the GTM, represented the instruments to achieve the goals set out in the Gas Regulation (EC) No. 715/2009 for a single energy market.

Overall, the GTM envisaged the amount of infrastructure that, if utilised efficiently, would enable gas to move freely across market areas towards where it is priced highest. In addition, the GTM defined measures for the harmonisation of the balancing system across Member States, and mechanisms to enhance wholesale natural gas market quality, namely the level of trading activity, liquidity, resilience, volatility and competitiveness, to better sustain hedging and price risk management. The PRISMA-platform was established in 2013 to auction in a transparent and homogeneous way the interconnection capacity across the 28 Transport System Operators (TSOs), corresponding to 70% of Europe's gas.

On the whole, the Gas Directives and Regulations aim to foster a well-functioning and transparent wholesale natural gas market by providing the legislative and regulatory framework, according to which natural gas trading should occur. In this context, natural gas trading hubs have been developed in the EU, as described in the next section.

1.3 Natural Gas Trading Activity

1.3.1 European natural gas physical hubs

European natural gas markets have developed around the National Balancing Point (NBP) in the United Kingdom (UK), which started trading in 1996 and represents the most mature hub in Europe. The NBP is a virtual trading location, i.e. any natural gas purchase and sell in the UK is supposed to occur at the NBP hub, where price is set out. This hub is the main EU natural gas pricing hub and thus the premier benchmark in Europe (Cummins and Murphy, 2015; Petrovich, 2015).

The Title Transfer Facility (TTF), located in the Netherlands, started trading in 2003, but only since 2012 it has been attracting participants, with increasing degree of price transparency and market liquidity. It is becoming an even more prominent hub in Europe, for

the purpose of price formation. Similarly to the NBP, the TTF is a virtual trading hub.
The Belgian Zeebrugge is the second gas hub in Europe, as it started trading in 2000, and a virtual hub. This hub is also the physical location where the pipeline *Interconnector*, joining the UK with the Belgian market, and consequently with the Continental Europe markets, converges. Whilst both the NBP and TTF hubs are widely used for financial hedging and risk management, Zeebrugge remains based on the balancing needs of the market participants, and/or spread trading between Zeebrugge, and either NBP or TTF prices (Heather, 2015).
NCG and GasPool are the two German hubs, which correspond to two market areas. Both started trading in 2009 although traded volumes have been increasing since 2014. Trading activity is mainly driven by spot/prompt trades. Futures trading is also increasing, mostly at the GasPool hub, because of the put into operation in 2012 of the Nord Stream pipeline linking Russia and Germany, and the consequently greater spread trading between GasPool, and either NCG or TTF.
The two French hubs, PEG North and PEG South, started trading in 2004 and 2015, respectively. Yet, PEG North attracts the greatest trading activity and has been growing since 2011.
Austria owns one of the most important trading points in Continental Europe, Baumgarten, which is a import processing plant on the Austrian/Slovakian border. Around one third of all Russian gas exports to Europe flows through Baumgarten towards Germany, Italy, Hungary and Slovenia, and the national market (Heather, 2015). This hub started trading in 2005. In 2013 a virtual hub, the VTP, was created for the Eastern market area. Trading at VTP is developing, even though the majority of trades is led by spread with the TTF, NCG or the Italian PSV hubs.
Trading at the PSV hub started in 2003, albeit a significant increase in traded volumes has been observed only since 2012. Currently, only a small percentage of gas is traded at PSV (0.3%, LEBA, 2016). Other European natural gas trading hubs are the Spanish AOC, the Danish GTF, the Polish VPG, the Czech VOB, which however are at early stages of their

development and barely trade.

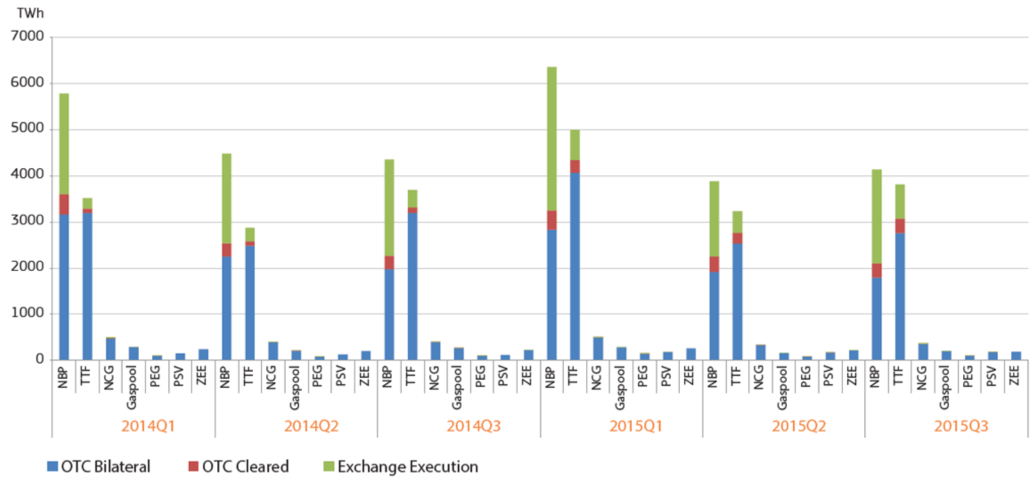
Overall, European gas hubs work primarily as physical hubs, that is as balancing hubs for market participants interested in clearing their physical positions, usually near to maturity and at delivery, and for the TSOs, which are required to balance the gas grid, mostly on a daily or intra-day basis. Therefore, trading at balancing hubs mainly involves spot/prompt markets. Spot prices are set according to the prevailing conditions of supply and demand. Published spot price indices are available for natural gas at different hubs from different providers (e.g. from ICIS, Platts), as well as listed across European energy exchanges (e.g. Powernext at the PEG North hub, ENDEX at the TTF hub, EEX at the NCG and GasPool hubs). Nevertheless, hubs are increasingly used as financial hubs to hedge risk and manage portfolios through derivative instruments. The main financial markets for the natural gas are described below.

1.3.2 Financial natural gas markets

The most important exchange-traded platform for the natural gas in Europe is the Intercontinental Exchange (ICE), which offers a wide range of derivative products, both physically and financially settled. These products include futures contracts and options. As stated by ICE (ICE, 2015b), futures contracts are for physical delivery through the transfer of rights in respect of natural gas at the trading hub. For a given frequency, delivery is made equally each day throughout the delivery period. Frequencies range from daily to yearly strips. Considering the UK natural gas futures market as an example, since it is the largest exchange-traded natural gas market in Europe, daily futures contracts include: up to forty-two daily contracts from day-ahead; one balance of the week; three weekends; five working days next week; one balance of the month. Trading of the daily contracts ceases at the close of the business day prior to the commencement of the delivery period. Strips at lower frequencies typically span: seventy-eight to eighty-three consecutive month contracts; eleven to thirteen consecutive quarters; thirteen to fourteen consecutive seasons; six consecutive years. Trading ceases at the close of business, two trading days prior to the first calendar day of the delivery month, quarter, season, or calendar (ICE, 2015c).

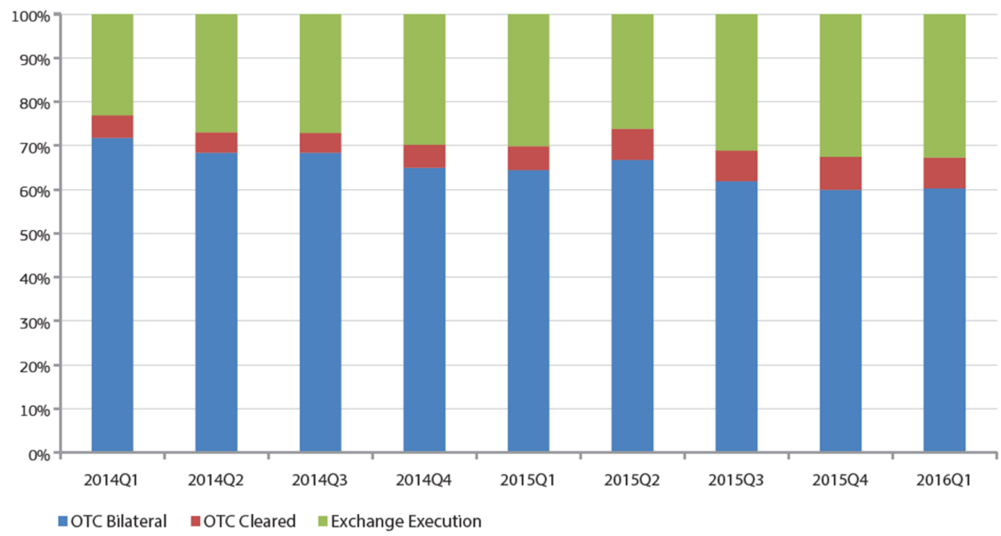
Whilst exchange-traded markets offer standardised contracts, over-the-counter (OTC) markets consist of non-standardised or bilateral agreements, which are concluded over the phone or, more often, through inter-dealer brokerage venues. OTC markets provide market participants with great flexibility by offering the possibility of tailoring derivative instruments to better fit individual hedging and risk management needs. Specifically, in the case of natural gas trading, OTC markets permit to adapt contract size, location, time of delivery and form of delivery, whether physical or cash settled, quality or heating value. Due to their nature, OTC markets are opaque and expose participants to higher counterparty risk, in case of insolvency, when compared to the exchange-traded markets, where default risk is borne by the exchange clearing house.

In Europe, natural gas trading is highly concentrated at the NBP and TTF hubs, where traded volume is almost one order of magnitude greater than the traded volume at the other European hubs, as shown in Figure 1.1, plot (a). On the whole, the two prominent hubs cover around 90% of hub traded volumes. Furthermore, with the exception of the NBP, where exchange-traded volumes almost equal OTC traded volumes, the OTC market represents the most important market across the Continental Europe hubs and covers roughly 60% of the total traded volumes (Figure 1.1, plot (b)). Nonetheless, exchanges are growing: whilst in the first-quarter of 2014 exchange-traded volumes were 23% of the total traded volumes, in the first-quarter of 2016, this share increased to 33%. During the same period, the share of cleared OTC volumes increased from 5% of the total traded volumes to 7% (Petrovich, 2015).



Source: European Commission: Quarterly report on European gas markets. OTC volumes include spot volume but exchange volumes do not.

(a) Traded volumes on the main European gas hubs



Source: European Commission: Quarterly report on European gas markets. OTC volumes include spot volume but exchange volumes do not.

(b) Share of trades volumes on the main European gas hubs

Figure 1.1: European wholesale gas markets

The derivative instruments that are traded on the exchanges and OTC markets are similar, namely: futures and forward contracts; options; swaps. Forward and futures contracts are the most basic hedging instruments. Forward contracts are OTC agreements that permit to buy or sell a certain amount of commodity at a fixed date in the future (delivery or maturity) and at a specified price. Futures contracts are standardised exchange-traded forward contracts. However, unlike forwards, where the payment occurs at maturity, futures are "marked-to-market" on a daily basis. That is, participants in the futures market have to adjust their positions by making partial payments to the exchange that reflect changes in the current futures price for the specified maturity. In addition, compared to forward contracts, which are mainly physically settled, futures contracts are mostly cash-settled; that is, natural gas is not delivered, but parties involved in the agreement exchange its market value. Furthermore, since the exchange works as a clearing house for futures contracts, participants on the exchange are not exposed to multiple counterparties and their associated credit risk. Despite negotiated bilaterally and subject to the counterparty risk, OTC forward contracts might be rebooked through a clearing house on a post-trade basis. The clearing house acts thus as a central counterparty to the transactions, similarly to the clearing and settlement process of the exchange-traded futures, therefore helping market participants to manage their credit risk exposure.

Although forward and futures contracts may reduce price risk, market participants may also ask for greater flexibility in risk management, for example to exploit upside risks while curbing downside risks. Options have been designed to provide this flexibility by giving the holder the right, but not the obligation, to buy (call option) or sell (put option) a certain amount of the commodity at a predetermined price, called "strike price" at any time up to the expiration date (American option) or only on the expiration date itself (European options). These instruments are mainly favoured by investors, such investment banks, hedge and pension funds, and are usually only traded in mature markets, with high liquidity and transparency. To date, options volumes are only recorded at the NBP and TTF hubs. Exchange-traded options account for 11% of the total exchange-traded volumes at the NBP, and 4% at the TTF. In the OTC markets, options account for around 6% of the total traded volumes at the NBP, and around 1% at the TTF (Heather, 2015).

Finally, swaps allow for the exchange of a pre-specified fixed price against a floating price, as from a published price index at the specified date. In the European natural gas markets, swap trading usually involves trade location and maturity, either between market participants or within the same portfolio (Heather, 2015).

1.3.3 Derivatives trading: The driving forces

During the last fifteen years, European natural gas markets have experienced increasing interdependence between physical and financial trading, which has been driven by the growing demand for natural gas, and the need for adequate transmission and storage capacity (Nijman, 2012; Cummins and Murphy, 2015). The unbundling of generation and supply from network ownership has increased the uncertainty of utilities and energy companies on market share and payback on investment, thus their exposure to price fluctuations (Pilipovic, 2007). Hedging and risk management by derivatives trading have then gained greater importance within European energy markets. Although the underlying of derivative contracts is physical, these contracts are often cash-settled, as mentioned above. Cash-settlement has favoured the participation of financial investors in physical markets as counterparties of commercial investors, namely utilities and energy companies.

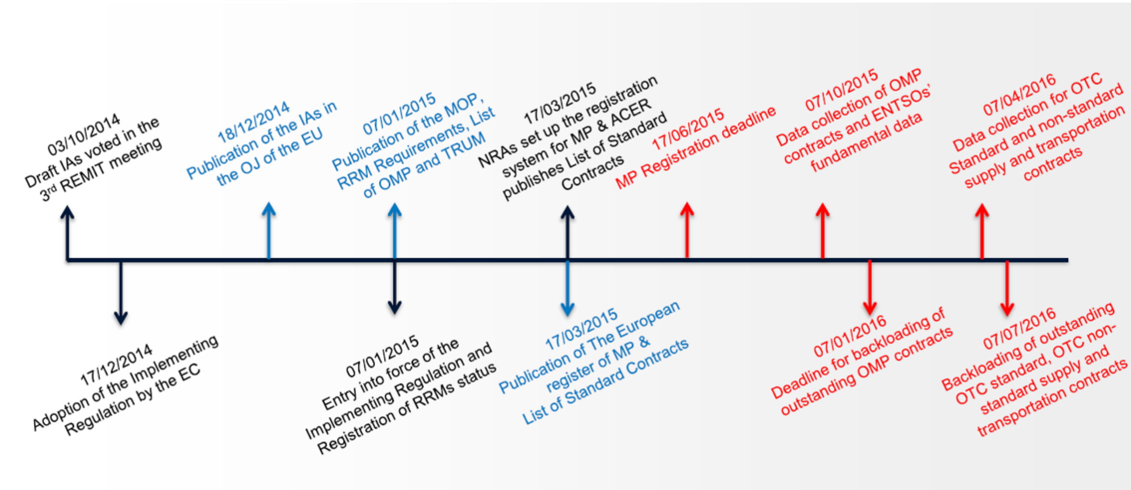
In the late 1990s-early 2000s, financial investors (investment banks, pension funds, hedge funds) showed interest in energy and other commodity markets, principally because of the low-interest rate and stock return environment that led them to exploit the benefits of portfolio diversification. In fact, commodity future returns have been shown to be negatively correlated with stock and bond returns, and positively correlated with inflation, thus implying that they behave differently from other financial asset classes during business cycles (Gorton and Rouwenhorst, 2006; Bhardwaj et al., 2015). Consequently, to maintain their desired returns on investments, financial investors switched from low-interest equity markets to the derivative commodity markets at that time. A related argument points to the diminishing returns in the stock markets that moved investors towards commodities as an alternative asset class. Again, derivatives provide financial investors with the opportunity for speculative behaviour. Derivatives are of interest to speculators because of their fix *versus* operational costs: it is easier and more profitable to purchase futures or options on large volumes than the physical asset. Derivatives trading permits the exploitation of arbitrage opportunities that arise from price differences for equivalent assets. Yet, exploiting these opportunities erodes them, thus facilitating price convergence.

Overall, the distinction between the reasons for commercial investors and financial investors to trade in energy and other commodity markets is blurred. Financial investors may be involved in energy trading to hedge other assets, while commercial investors may also engage in "speculative hedges". Since the collapse of Enron and the California's power crisis in 2001, energy derivatives trading has been drawing the increasing attention of policy-makers, who are concerned about the detrimental effects that credit risk may have on the physical supply of energy (Brunet and Shafe, 2007). These concerns became particularly acute in the aftermath of the 2008-09 financial crisis, when OTC derivatives played a crucial role in spreading systemic risk among interconnected international financial markets (Larosière et al., 2009), thus highlighting the opacity and the lack of oversight of those markets. Consequently, new financial regulations referring to OTC transactions, and more broadly to financial markets, have been introduced, in the attempt of curbing systemic risk through greater transparency and mandatory clearing.

1.3.4 European regulation for trading: REMIT and other regulations

To achieve stability in energy markets, the European Commission has set a new regulatory framework, aimed at improving transparency, in particular in the most opaque OTC markets, and curbing price volatility in energy markets. The most important initiative regulating energy markets is Regulation (EU) No. 1227/2011 on wholesale Energy Market Integrity and Transparency (REMIT). Other initiatives that involve financial markets and affect, in some form, energy and other commodity derivatives trading include Regulation (EU) No. 648/2012 on the European Market Infrastructure Regulation (EMIR); Regulation (EU) No. 596/2014 on Market Abuse (MAR); Markets in Financial Instruments Directive 2004/39/EC (MiFID), and its updated version, Directive 2014/65/EC (MiFID II); Market Abuse Directive 2003/06/EC (MAD), and its updated version, Directive 2014/57/EU (MAD II).

REMIT is designed to increase transparency and prevent market abuse in the wholesale natural gas and electricity markets (oil and other energy sources are excluded), including derivative markets. In particular, REMIT introduces a reporting regime for wholesale natural gas and electricity transactions to detect and prevent market abuse. According to REMIT, market participants, including TSOs, suppliers, traders, producers, brokers, utilities and industrial users, who trade energy commodities and derivatives are required to disclose trading information, and operation and capacity plans to ACER, in order to improve cross-border market monitoring. Since ACER is the European energy regulatory authority, it is best placed to carry out the monitoring because it has a union-wide view of natural gas and electricity markets. NRAs thus are expected to pursue market monitoring at a national level and additional data collection for local purposes. The obligation to publish inside information and prohibition of market abuse is in force since December 2011. The Implementation Act, however, was published on 18 December 2014. From 7 October 2015, the obligation requires the reporting to ACER of all natural gas and electricity transactions with delivery in the EU, which are executed at organised marketplaces, including matched and unmatched orders. From 7 April 2016, the reporting obligation is extended to other wholesale contracts (OTC standard and non-standard supply and derivative contracts, transmission contracts) and other fundamental data (e.g. planned energy generation). The REMIT implementation timelines is shown in Figure 1.2.



Source: CME Group, *REMIT-Regulation on wholesale energy market integrity and transparency.* Webinar, 15^{th} November 2015.

Figure 1.2: REMIT implementation timelines

EMIR, in force since August 2012, came into effect on 12 February 2014. This regulation introduces: the obligation to report OTC derivatives, including commodity derivatives, to trade repositories; a clearing obligation for eligible OTC derivatives; measures to reduce counterparty credit risk and operational risk of bilaterally cleared OTC derivatives; common rules for central counterparties and trade repositories. The goal of EMIR is threefold: (i) reporting of risk; (ii) clearing of risk; (iii) mitigation of risk. OTC transactions are required to be reported to a central trade repository, accessible to the European Securities and Markets Authority (ESMA) for the purpose of monitoring and publication. Commercial investors are not subject to clearing obligations when the OTC position notional value is below e 3 billion, which is a predefined threshold that represents a systematic level of risk, beyond which the firm's activity becomes relevant for financial stability.

MiFID introduced a transaction reporting regime across the EU in 2007, which is set to be expanded in 2018, when MiFID II should come into effect. MiFID and MiFID II cover all financial instruments. Their scope is to improve oversight and transparency of financial markets, including commodity markets, in order to (i) ensure their function for hedging and price discovery; (ii) guarantee fair competition between trading venues; (iii) foster market efficiency and lower costs, in particular following the most recent developments in the markets structure and technology, such as the high-frequency trading.

MAD, MAD II and MAR aim to increase the integrity of financial markets by prohibiting market abuse that may be led by insider trading or market manipulation. MAD was originally adopted in 2003. Both MAR and MAD II were published in 2014 and became applicable on 3 July 2016 to reinforce market monitoring and surveillance, following technological changes in financial trading.

On the whole, whilst REMIT, MiFID and MAD/MAR reporting initiatives are mainly focused on market abuse, the reporting scheme under EMIR principally aims to curb systemic risk in specific markets. Yet, REMIT provides a EU-wide reporting framework specific to EU wholesale natural gas and electricity markets to guarantee participants with fair and transparent prices for the benefit of European consumers. Therefore, REMIT reporting has a broader scope than the other financial regulations and directives, that is to ensure energy markets efficiency and competitiveness. The implications of REMIT for natural gas markets will be investigated later in the empirical studies. In the next section, features and evolution of European natural gas prices are described.

1.4 European Natural Gas Prices

1.4.1 Long-term contracts and oil-indexation

The origin of the European natural gas industry can be dated back to 1959, when the giant field Groningen was discovered in the Netherlands, followed by further discoveries in the North Sea. The Netherlands began thus to export natural gas to France, Belgium and Germany in 1962, according to a pricing mechanism known as the *Nota de Pous*, named after the Dutch Minister of Economic Affairs Jan Willem de Pous, who was the main promoter of the natural gas continental market. This mechanism was based on inter-fuel competition between energy sources on a sectorial level. In the 1960s, the European energy industry was in the process of switching from coal to gasoline for domestic heating. Natural gas prices were therefore set based on the gasoline prices and the distance between the end-user market and the Dutch border; thus, they were periodically renegotiated according to changes in the market conditions.

The development of the European natural gas industry in the 1960s was mostly led through large and creditworthy buyers, who were able to bear the required investment for the production, transmission, storage and distribution of gas from the fields to the final markets. At that time, volume risk was the main risk, which was defined as the difference between contracted volumes and natural gas demand growth. This risk was mainly driven by the price uncompetitiveness of natural gas relative to its competing fuels, or economic downturns. Volume risk fostered specific bilateral relationships between the Dutch Ministry and its counterparties, in the form of long-term contracts that were legally binding, and subject to international arbitration. In the following decades, these contracts were progressively adopted by the Former Soviet Union (FSU), Algeria and Norway in bilateral negotiations with all large-scale European gas importers.

Long-term contracts could cover periods from 10 to 25 years or more (Cummins and Murphy, 2015) and were designed to provide consumers and suppliers with volume certainty. Specific provisions were then introduced to provide market participants with some flexibility and allow them to manage volume risk. These provisions include:

- Take-or-pay (ToP): This provision guarantees the seller with a return on the investment. Under take-or-pay contract terms, an annual contract quantity (ACQ) is fixed to be delivered each year for the duration of the contract. The buyer agrees to (i) either take, and pay, a minimum amount of the ACQ each year, which is usually set out in 80%-90% range (Yafimava, K., 2014); (ii) or pay the applicable contract price for such ACQ when this is not taken during the applicable year. That is, the payment for the minimum ACQ is required regardless of the amount actually taken by the buyer, who therefore *de facto* assumes the volume risk.

- Swing: This is a take-or-pay type provision, giving the buyer the right to call for the quantity of gas to be delivered on a daily basis (DCQ), with pre-specified minimum and maximum boundaries. These boundaries are either narrow (±10%) or wide, and spanning from a minimum of 0% to a maximum of 200% of the DCQ (Cummins and Murphy, 2015), thus providing the buyer with volume flexibility.

- Pricing mechanisms: Long-term contracts link natural gas price to other energy commodity prices. Usually, these are heating oil, crude oil, fuel oil, but also coal. Indexation mechanisms are set out in such a way that a lagged six- to nine-month moving average is included. Pricing mechanisms are also set indexed to the inflation rate, by including the average US dollar/Euro exchange rate over a six-month period (Platts, 2016). This allows natural gas prices in long-term contracts to respond and adjust to evolving market conditions.

- Interruption: Interruption provisions allow suppliers to cut natural gas deliveries to their counterparties, thus permitting the management of maintenance and disruption to the fields. Usually, a maximum period is established for the interruption with no penalties, which for instance in the UK market is fixed in 45 days in one year (Cummins and Murphy, 2015).

This natural gas contracting structure was in place until the past decade in Continental Europe, though market players may have used different mechanisms, based on bilateral agreements. Furthermore, this structure does not include additional discount factors that may have been introduced to account for the most recent renegotiations in the natural gas industry, which have been taking place since the 2008-09 economic downturn (Platts, 2016).

Oil-linked price mechanisms were mostly used in Continental Europe. In the United Kingdom natural gas pricing was based upon various factors, which resulted in prices between producers and the state monopoly British Gas Corporation that were partly indexed to oil and partly to inflation (Stern and Rogers, 2014). With the liberalisation of the British market and the creation of the NBP as a trading hub in 1996 - a decade before the liberalisation of European markets -, natural gas prices in the UK are mostly driven by gas-on-gas competition, that is by dynamics in the fundamental values of supply and demand. In

Continental Europe, natural gas remains partially traded via long-term contracts and this situation is expected to continue for some years because of the duration of remaining contracts (ACER, 2015b). Yet, in recent years, there has been a shift towards short-term hedging of gas at hubs. This has resulted in an increase of gas-on-gas competition and hub-traded volumes, either driven by financial arbitrage and price risk hedging, or as physical source of gas. In the next sections, the gas-on-gas pricing mechanism is reviewed.

1.4.2 Gas-on-gas competition and natural gas hub pricing

Gas-on-gas competition is influenced by a variety of factors, among which long-term contracts, through the flexibility component of the ToP volumes. This, together with the fact that oil prices have been historically used in pricing long-term contracts, explain the traditional correlation between oil prices and gas hub prices (Asche et al., 2013). However, there is also evidence that hub prices have become increasingly driven by demand fluctuations and flexibility of supply, such as long-term contract volumes not subject to ToP obligations, divertible LNG deliveries, storage withdrawals, and the direct hub sales of upstream producers (Timera-Energy, 2016). All these factors interact in setting natural gas hub pricing and driving gas-on-gas competition. Yet, the impact of economic downturn on European gas demand, the wave of new LNG supplies, and the dramatic increase in shale gas supply from the US have led to sharp falls in European natural gas prices, while compromising the traditional long-term natural gas contracting structure. In fact, during 2009-11, European gas importers faced financial difficulties to pay for minimum contracted quantities (Stern, 2009). Therefore, contract renegotiations have been in place in Continental Europe since the economic downturn, which have also entailed the introduction of hub-indexation in long-term contracts, thus leading to some realignment of natural gas contract prices with spot prices.

According to International Gas Union (2016b), since 2005 natural gas pricing in Europe has been constantly moving from oil-indexation to hub-indexation , with the share of gas sold priced at hub increasing from 15% in 2005 to 64% in 2015, In the same period, oil-indexation declined from 78% in 2005 to 30% in 2015. This change reflects the expiry of long-term contracts, or their renegotiation to include hub-indexation, and in some cases a reduction in the take-or-pay quantities. Furthermore, a decline in the volume of gas imported under the traditional oil-linked contracts occurred in the last decade, which was replaced by imports of spot gas, with the consequent growth of volumes traded at European hubs. The trend towards hub-indexation has been reinforced by the decline in the oil-linked domestic production in the UK, which has been replaced by pipeline and LNG imports that are hub-linked (Stern, 2009; International Gas Union, 2016b).

The evolution of European natural gas pricing during the period 2005-15 is shown in Figure 1.3, where OPE (Oil Price Escalation) represents the share of gas sold oil-linked in Europe; GOG (Gas-On-Gas) is the share of gas sold hub-linked; BIM (Bilateral Monopoly) represents prices set according to bilateral agreements; NET (Netback From Final Product) is the price received by the gas supplier as a function of the price received by the buyer for the final product the buyer produces, as for instance the feedstocks in chemical plants (ammonia or methanol); RCS (Regulation; Cost of Service) represents regulated prices; RSP (Regulation: Social and Political) is the price set out, on a irregular basis, by a Ministry; RBC (Regulation: Below Cost), the price set below the average cost of producing and transporting, often used as a form of state subsidy to the population; NP (No Price) when the gas is provided free to the population and industry.

[redacted]

Source: International Gas Union- Wholesale Gas Price Survey, May 2016

Figure 1.3: Evolution of the European natural gas pricing from 2005 to 2015

Changes in the natural gas pricing mechanisms have been heterogeneous across European regions. North-West Europe - Belgium, Denmark, France, Germany, Ireland, Luxembourg, the Netherlands, the United Kingdom - has seen the greatest change in the pricing mechanism, with a complete reversal between oil- and hub-linked positions: from 72% oil-indexation and 27% hub-indexation in 2005 to 8% oil-indexation and 92% hub-indexation in 2015, as a result of increased hub trading and contract renegotiations. By contrast, in Mediterranean countries - Greece, Italy, Portugal, Spain, Turkey - oil-indexation has only declined from 100% in 2005 to around 63% in 2015, whilst hub-indexation has recently increased from nothing to around 32% (International Gas Union, 2016b). This latest change reflects increased spot LNG imports in the region and some spot pipeline imports into Italy, as well as changes in the pricing of domestic production and the renegotiation of the main Russian contracts in Italy. Consequently, hub pricing and gas-on-gas competition are spreading heterogeneously across Europe, also in response to the international gas market dynamics. Nonetheless, different levels of liquidity across markets, and the presence of long-term contracts and oil-indexation may entail different demand/supply price signals across European hubs, with implications for the convergence towards a single market.

1.5 Conclusions

The goal of this chapter was to offer an overview of the process towards the liberalisation of European natural gas markets and its implications for market participants and policy-makers. From the perspective of the regulator, the liberalisation and development of a single European natural gas market were viewed as a response to concerns regarding the efficiency and competitiveness of the European natural gas industry in an increasingly globalised market. Yet, this process has brought changes in the business models and strategies in the European natural gas industry, which are influenced by a number of factors. These factors include an evolving regulatory framework, price formation mechanisms and risk management strategies, competition and market integration, which can be viewed as a challenge, an opportunity, or a threat for market players and policy-makers. Gas trading globalisation, greater uncertainty in the European natural gas demand, profitability of natural gas investments, climate change and the challenging regulatory framework have posed new risks for market players and may affect the competitiveness and efficiency of the EU's energy markets pursued by the regulator. With increasing hub trading and hub prices becoming referential prices, it is important to investigate what may affect hub pricing. The reminder of this dissertation focuses on three critical issues of European natural gas markets - liquidity, price volatility and market integration, which have implications for market participants, interested in risk management and investment decisions, and are critical for policy-makers, concerned about the overall quality of European energy markets.

2

Assessing Liquidity Dynamics in the Forward Markets for Natural Gas*

2.1 Introduction

The liberalisation of the natural gas sector has led to greater price movements, thus creating price risk for market participants. An increasing exposure to price risk has resulted in higher demand for forward contracts, which are used for hedging and risk management strategies. In this respect, the level of liquidity of forward markets, which is a barometer of marker quality, becomes relevant since it determines whether market participants are able to hedge their exposure in a competitive and efficient way (ACER, 2015b).

Liquidity is defined as the ability to match buyers and sellers at the lowest transaction cost (O'Hara, 1995), and reveals whether a market offers sufficient opportunities for trade and whether each single transaction has limited impact on market prices. The importance of liquidity is highlighted in the literature on market microstructure, which however has been mainly focused on financial assets in different markets, such as stock and bond markets (Chordia et al., 2000, 2005b), or foreign-exchange markets (Bessembinder, 1994; Banti

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et al., 2012; Danielsson and Payne, 2012). Overall, the market microstructure literature shows that low liquidity leads to lower asset prices and higher rate of returns, which are required to compensate investors for bearing the cost of liquidity (Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996; Pastor and Stambaugh, 2003; Hasbrouck, 2009). Consequently, in the natural gas markets, and more broadly in energy markets, liquidity can provide investment signals to market participants and reduce the possibility of price manipulation. Conversely, illiquidity may act as a barrier to market entry and is a source of competitive disadvantage to small suppliers, thus compromising market competitiveness and efficiency.

To date, little attention has been devoted to study liquidity in energy markets. The main motivation of this chapter is to investigate the dynamics of liquidity in the one-month-ahead forward market of the UK National Balancing Point (NBP, hereafter), which is the main natural gas trading hub in Europe (Cummins and Murphy, 2015; European Commission, 2015) and can thus represent the European natural gas market. The use of measures from the financial markets, which capture different dimensions of liquidity, is investigated. Thus, this chapter assesses whether such measures, which have been designed and applied to analyse liquidity in financial markets, are valuable for the natural gas market. The links between liquidity, trading activity and price volatility are also considered to assess how trading can affect market quality in the NBP forward market. A vector autoregressive (VAR) representation is adopted, as in previous studies on financial markets (Chordia et al., 2005b; Danielsson and Payne, 2012). However, in contrast to these studies, a time-varying approach is developed in order to identify changes that might have occurred in liquidity, and in its links with trading activity and price volatility. Finally, the effects of the recent regulation, REMIT, on the NBP forward market liquidity are investigated. Although higher transparency can improve liquidity by reducing transaction costs and lowering barriers to market entry (European Commission, 2004; Bessembinder et al., 2013), REMIT's effects on liquidity and other aspects of energy market quality are unknown (Nijman, 2012).

The remainder of this chapter is organised as follows. In Section 2.2, the literature on liquidity measurement is reviewed, and the debate on the new regulatory framework implied by REMIT is summarised. Section 2.3 states the research questions. Section 2.4 describes the methodologies. Data are presented in Section 2.5. Results are reported in Section 2.6 and discussed in Section 2.7. Section 2.8 concludes, assesses the implications for the literature and sets the future research agenda that follows from this chapter.

2.2 Literature Review

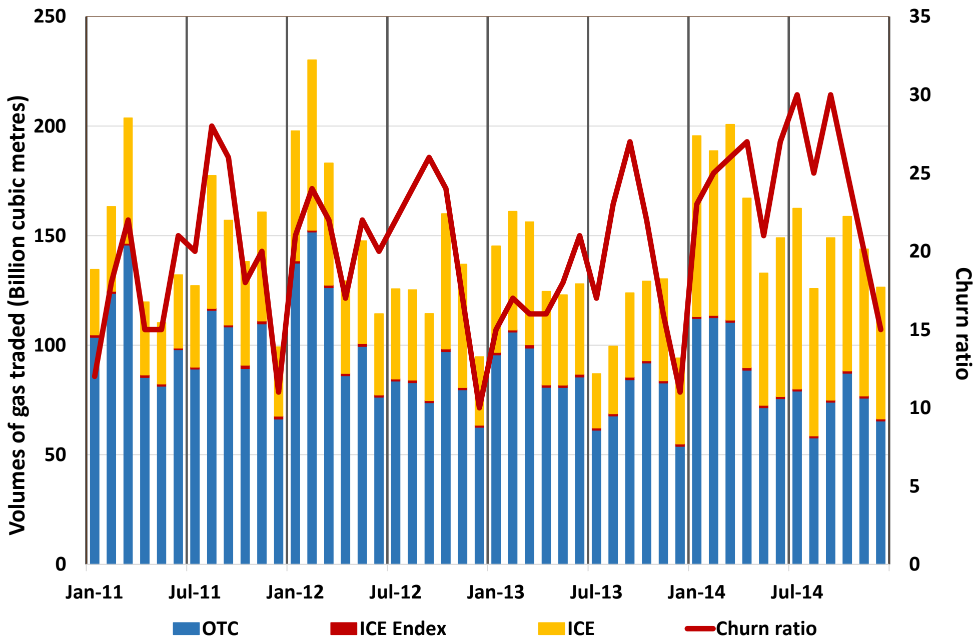
2.2.1 Liquidity in energy markets

Practitioners in the natural gas and power markets usually refer to the *churn ratio* as the measure of market liquidity. The *churn ratio* is the ratio of trading volumes to physical deliveries after transactions: the higher this ratio, the higher is liquidity. Intuitively, this measure reveals the vitality of a market and can be considered as equivalent to the turnover ratio, which is the value of shares traded divided by market capitalisation and is often used to assess liquidity in stock markets. The *churn ratio* is simple to calculate and permits to compare liquidity across geographically different markets or hubs, and across commodities (Ofgem, 2009). However, this is a trade-based measure and like other trade-based measures, such as the turnover ratio, the trading frequency, or the trade size, may be a poor measure of market liquidity (Aitken and Comerton-Forde, 2003). Although such measures are supported by the empirical evidence of a positive correlation between liquidity and trading activity (Fleming, 2003), high trading activity may be linked to high volatility, which would reduce liquidity (Karpoff, 1987). Furthermore, trading activity can be high when a market is in crisis and liquidity is actually low (Roll, 2005).

In the natural gas and power markets, trading activity is also expected to be driven by seasonality and weather-dependent events, which reflect in the churn ratio. As illustrated in Figure 2.1, on average higher *churn ratio* is observed in the summer (July-September) when traded volumes are lower compared to the winter months. This suggests that higher physical deliveries compared to traded volumes are observed in December and, to less extent, in April. Whilst low *churn ratios* in December would be reasonably driven by the historically low month-on-month trade observed during this period at European hubs (Platts, 2016), the dynamics of the ratio in April and during the summer can be explained by the annual storage cycle.

The first week of April marks the start of the storage-year, that is when storage facilities switch from winter withdrawal (at higher winter prices) to injection (at lower summer prices) (Timera-Energy, 2016). By contrast, the first week of November marks the shift from the injection to withdrawal season. As inventory level increases during the summer, one can speculate that physical deliveries reduce relative to the financial trading, thus increasing the *churn ratio*. Furthermore, since the spread between summer and winter prices is a signal for storage-capacity holders and investors in the natural gas markets, shifts in the trading activity may occur to hedge against short-term fluctuations of this spread before the start of the injection and withdrawal. These shifts could explain the month-on-month increases in the *churn ratio*, as observed in February, and to less extent in March, and in September.

Since it is mainly driven by changes in the trading volume relative to the physical deliveries, the *churn ratio* may be a misleading measure of liquidity. In fact, Newbery et al. (2004) highlighted the need to consider and investigate different factors that may impact liquidity in energy markets: volume, price volatility, number of market participants, presence of different prices for the same product, bid-ask spread and transaction costs; because any of these factors contributes to the optimal market design and its performance.



Source data: Ofgem-Data portal

Figure 2.1: Monthly NBP traded volume and churn ratio

2.2.2 Liquidity measurement

Despite the conciseness of the definition of liquidity, a rigorous and empirically relevant measure remains a challenge, due to the multiple dimensions implied by its definition. According to Kyle (1985), liquidity encompasses different transactional properties of a market: tightness, i.e. "the cost of turning around a position over a short period of time"; depth, "the size of an order flow innovation required to change price by a given amount"; and resiliency, "the speed with which prices recover from a random, uninformative shock" (pp. 1316). Jointly, these properties highlight how trading implies a cost. Following the availability of high-frequency intraday data, different measures of spread and price impact have been introduced, which are also defined order-based measures (Hasbrouck, 1991; Chordia et al., 2000; Goyenko et al., 2009).

Measures of spread

The quoted bid-ask spread and the effective bid-ask spread (Roll, 1984; Stoll, 1989) are common proxies for tightness. Their intuitive meaning is derived from a microstructure model where customers trade only with market-makers and the quoted bid-ask spread is centred, on average, on the fair asset value. According to this model, in each trade customers bear a transaction cost that is equal to the difference between the actual price and the bid or ask price (Demsetz, 1968). The quoted bid-ask spread represents, thus, the transaction cost paid by the costumer to the market-maker for a round-trip, that is a purchase followed by a sale of the same amount. However, Stoll (1989) argued that even when trades occur between customers and market-makers, the quoted bid-ask spread can overstate the actual transaction costs if a subset of customers is better informed than the market-makers, or if the market-maker adjusts the bid-ask spread to control her inventory level. Therefore, Huang and Stoll (1996) proposed to replace the quoted bid-ask spread with the effective bid-ask spread, which they defined as the adjustment of bid and ask quotes to trades. It is noteworthy that in an earlier study, Amihud and Mendelson (1986) had also suggested an alternative measure of spread, namely the relative quoted bid-ask spread, which is defined as the quoted bid-ask spread divided by the quoted midpoint, i.e. the average of the bid and ask quotes. According to the authors, this measure assesses the cost of immediacy as a measure of transaction costs.

Since their introduction, measures of spread have been adopted in different empirical studies of transaction costs in financial markets (Bessembinder, 1994; Goyenko et al., 2009; Bessembinder and Venkataraman, 2010; Corwin and Schultz, 2012). When considering commodity and energy markets, the effective bid-ask spread was first used by Locke and Venkatesh (1997) to measure transaction costs in the futures markets at the Chicago Mercantile Exchange (CME). More recently, Marshall et al. (2012) employed the quoted bid-ask spread and the effective bid-ask spread to investigate transaction costs in commodity markets. In addition, they assessed the effectiveness of some low-frequency proxies for the spread measures when high-frequency data are unavailable, or when computationally intensive liquidity measurement with high-frequency data is not worthy. In a subsequent study, Marshall et al. (2013) also adopted measures of spread to investigate common and systematic drivers of liquidity, and the link between commodity and stock market liquidities. More specifically in energy markets, Frestad (2012) used the quoted bid-ask spread to evaluate effectiveness and costs of hedging strategies in the Nordic power market. Overall, assessments of tightness as a dimension of liquidity appear to have been neglected in studies of natural gas markets.

Measures of price impact

In a high-frequency setting, several authors (e.g. Pastor and Stambaugh, 2003; Sadka, 2006; Acharya et al., 2009) have measured price impact to investigate the other two dimensions of liquidity: depth and resiliency. Price impact is defined as the temporary change in transaction prices that follows an order flow, where the order flow is defined as the signed volume (Pastor and Stambaugh, 2003). Hence, following a shock or an unexpected trade, impulse response functions can be used to determine the speed of convergence of prices towards their pre-shock equilibrium level. This approach was taken, for instance, by Hasbrouck (1991); Dufour and Engle (2000). By contrast, Hasbrouck (2009) proposed a measure of price impact defined as the price change associated with the aggregated signed square-root dollar volume within the same time interval, whilst Goyenko et al. (2009) measured price impact based on changes in the quote midpoint after a signed trade. Order flow, defined as the difference between the number of buy and sell market transactions, was used as an indirect measure of price impact and found to be related to quote and price changes (Hasbrouck, 1991; Evans and Lyons, 2002; Payne, 2003; Evans, 2010; Chen et al., 2012). More recently Banti et al. (2012) developed a measure of price impact based on the notion of expected return reversal.

To date, measures of price impact have been generally investigated in financial markets, particularly in stock and foreign-exchange markets. Their application to energy and other commodity markets may be challenging due to the difficulty of collecting high-frequency data on order flows and traded volumes. As a result, how to measure depth and resilience in energy markets is a research question, which to the best of our knowledge remains to be addressed in the context of European natural gas markets.

2.2.3 Liquidity and the implications of the market microstructure theory

The ability of matching buyers and sellers at the lowest transaction cost, implied by the definition of liquidity, relies on the trading mechanisms. The literature on market microstructure analyses how these mechanisms affect assets pricing and focuses on what O'Hara (1995) called the "dark side" of liquidity (p. 216). Lack of liquidity may impose costs on market players and some investors may exit the market, thus creating instability and barriers to potential new entrants. Hence, it is important to understand the dynamics of liquidity in a market (Chordia et al., 2005b).

The founder of the market microstructure theory, Garman (1976), argued that trading entails a flow of orders to buy and sell that may generate temporal imbalances between demand and supply. These imbalances affect the dynamics of liquidity over time, highlighting the importance of analysing the role of inventory. Amihud and Mendelson (1980) concluded that bid and ask prices depend on changes in the dealer's inventory positions and are increasing functions of her inventory imbalances. Their argument led to the problem of the risk faced by the dealer in optimising her inventory level. In the study of Stoll (1978), the dealer provides a service in the form of immediacy supply, which must be compensated. The cost of this immediacy is given by the bid-ask spread, which is the sum of: (1) holding costs, i.e. the price risk and opportunity cost of inventory; (2) order costs, the costs of arranging, recording and clearing transactions; and (3) information costs, which arise if traders have superior information which adversely affect the dealer's expected returns. In particular, holding costs guarantee the dealer's expected utility in spite of transactions that tend to move her away from the optimal inventory level, and may depend on the order flow and the traded asset return volatility.

By contrast, the informational-based approach to the market microstructure relies on the theory of adverse selection to explain the bid-ask spread (Bagehot, 1971). The spread "reflects a balancing of losses to the informed with gains from the uninformed" (O'Hara, 1995, p. 54). Therefore, the dealer's problem reduces to the optimisation of gains or losses in a dynamic perspective, where order flow is not exogenous but conveys information. That is, trading activity from informed traders represents the way in which information is spread in a market, or how uninformed traders can infer information on the asset fair value. Accordingly, order flow and trading activity provide "signals" (Glosten and Milgrom, 1985; Easley and O'Hara, 1987) and asset pricing is no longer independent of private information on the asset fair value, which is impounded in the order flow. Consequently, asset prices are affected by order flow and are not independent of past trading activity. The bid-ask spread reflects this dynamic of the price discovery and is a compensation for trading with better-informed traders.

Overall, inventory- and informational-based approaches to market microstructure imply that high trading activity can reduce market liquidity temporarily (inventory cost) and may move asset prices permanently (informational cost). Hence, according to the market microstructure theory, co-movements in trading activity, asset returns volatility and liquidity should be analysed.

In the early literature on liquidity in financial markets (Benston and Hagerman, 1974; Stoll, 1978), volatility and order flow were assumed to determine liquidity. The idea behind this stream of research is that the higher the asset return volatility, the higher the inventory risk, the lower is liquidity. These expectations are reflected in the bid-ask prices, which in turn depend on the order flow. Yet, liquidity was shown to influence equilibrium stock prices and expected returns (Brennan and Subrahmanyam, 1996; Brennan et al., 1998; Amihud, 2002), while both liquidity and asset returns were found to be affected by order flow and imbalances in the stock markets (Chordia et al., 2002).

Using a vector autoregressive (VAR) representation, Chordia et al. (2005b) found stock and bond market liquidity to be driven by returns and their volatility, as well as order imbalances. A negative correlation between liquidity and returns in stock markets was found by Hasbrouck (1991), in a VAR setting, and by Hasbrouck (2009), through a Bayesian Gibbs approach. In the foreign-exchange market, similar evidence was provided by Bessembinder (1994), who used different measures of spread and price impacts, and by Danielsson and Payne (2012) through a VAR representation. Order flow was used, for instance, by Evans and Lyons (2002) as a measure of liquidity to explain the dynamics of asset prices. Nevertheless, when academic studies of energy markets are considered, the assessment of the correlations between liquidity, return volatility and trading activity appears to have been neglected.

2.2.4 Implications of new rules aimed at greater transparency in energy markets

Although increased transparency has the potential to reduce transaction costs and improve the ability of regulators and practitioners to monitor the markets (European Commission, 2004; Boehmer et al., 2005; Bessembinder et al., 2013), the effects of greater transparency are ambiguous (Degryse et al., 2015). Higher transparency may lead to lower liquidity, because better informed participants may be reluctant to publish orders and disclose their information advantage (Harris, 1997; Madhavan et al., 2005). It may also be that transparency reduces liquidity only in case of large size transactions, which disclose greater information relative to small size transactions (Elstob, 2011).

The publication of fundamental data removes an important information advantage that energy companies have had over investors. Large utilities and energy companies can affect the physical amount being traded, whereas other participants are unlikely to have this power. In fact, studies of the relationship between liquidity and asset returns by Amihud (2002) and Pastor and Stambaugh (2003) have shown that a less transparent market offers profit opportunities for those parties with greater knowledge.

High information asymmetries entail high risk and financing costs, which are barriers for new entrants. Transparency should therefore foster competition and increase liquidity. Yet, if energy markets are rendered more transparent, a question remains concerning the consequences for financial investors. The amount of reporting implies high administrative costs for market participants, which may increase rather than reduce transaction costs. Higher transaction costs can make energy markets less attractive for investors. A reduction of trading activity from non-physical traders could reduce liquidity and stability, thus potentially harming the regulator's goals (CEER, 2015).

Overall, there are competing views on the impact of higher transparency in energy markets, which are of particular importance when the effects of REMIT are considered. REMIT is designed to increase transparency and prevent market abuse in the wholesale energy markets, including derivative markets. Nonetheless, higher transparency could affect trading activity, liquidity, prices and thus the strategic choices of energy companies (Nijman, 2012). By analysing the evolution of liquidity in the one-month-ahead NBP forward market, this chapter also aims to assess which of the above views on the impact of REMIT is more prevalent.

2.3 Research Questions

Given the lack of literature on liquidity in energy markets and the questions posed by the *churn ratio* as measure of liquidity, the following research questions are addressed in this chapter:

1. Are measures of spread and price impact used in financial markets useful to assess different dimensions of liquidity, and their dynamics, in the one-month-ahead NBP forward market?
2. What are the potential drivers of liquidity?
3. Have regulatory changes and higher transparency affected the time series behaviour of liquidity?

Since it provides investment signals to market participants and reduces the likelihood of price manipulation, assessing liquidity and its dynamics in energy markets is relevant not only to market participants, interested in the cost of hedging and risk management decisions, but also to regulators and policy-makers, concerned about market quality. In the next section, the methodological approach that is used to address the stated research questions is described.

2.4 Methodology

2.4.1 Measuring Liquidity

Measures of spread

One of the simplest and most intuitive liquidity measures is the quoted bid-ask spread, which is the difference between the best quoted ask price and the best quoted bid price (Amihud and Mendelson, 1986). However, this measure does not capture transactions that are executed at prices within the bid and ask quotes (Stoll, 1989; Bessembinder, 2003). Moreover, when OTC markets are considered, active market-makers, who post firm bid and ask quotes, are absent. Quotes are therefore indicative and tradable mid-market prices, which are provided by the broker based on actual trading orders and expressions of interest. In such a situation, a more reliable measure of transaction costs is the effective half-spread, since it reflects negotiated transactions either inside or outside the indicative quotes.

The effective half-spread measures transaction costs as the difference between actual transaction prices and bid-ask midpoints (i.e. midquotes) from the most recent bid and ask quotes, which are viewed as a proxy for the fair value of the asset (Bessembinder, 2003; Foucault et al., 2013). The effective half-spread can be specified either in absolute basis points or as a percentage of the midquote (Bessembinder, 1994; Goyenko et al., 2009; Bessembinder and Venkataraman, 2010; Corwin and Schultz, 2012). In this chapter, the percentage effective half-spread (EHS) is used, which is defined as follows:

$$EHS_\tau = D_\tau \left(\frac{P_\tau - M_\tau}{M_\tau} \right), \tag{2.1}$$

where P_τ is the price of the τ^{th} transaction, evaluated at the trading time and M_τ is the midquote at the same time. D_τ is the transaction direction indicator taking values 1, for buyer-initiated transactions, and -1, for seller-initiated transactions. In the financial literature, this indicator is usually set according to the Lee and Ready (1991) algorithm (Goyenko et al., 2009; Foucault et al., 2013). A transaction is classified as buyer-initiated if its transaction price is closer to the prevailing ask quote than bid quote, and as seller-initiated, otherwise. If a transaction is priced exactly at the midquote: it is defined buyer-initiated when its price is higher than the price of the previous transaction ("uptick"); conversely, it is classified as seller-initiated ("downtick"). Since the effective half-spread recognises that transactions can occur at prices other than those quoted (the midquote), it estimates the transaction cost actually paid by a liquidity demander, or the gross revenue earned by the liquidity supplier.

According to the market microstructure theory, the bid-ask spread must cover three costs that are borne by liquidity suppliers: order-processing costs, inventory costs, and asymmetric-information costs. As explained by Stoll (1978), the intuition behind inventory costs, which represent the non-informational component of the effective spread, is that transaction costs should result only in a temporary deviation of the price from the asset fair value. This temporary component is observed in a price reversal after the transaction (Bessembinder and Venkataraman, 2010), and can be captured by the percentage realised half-spread (RHS), which is defined as:

$$RHS_\tau = D_\tau \left(\frac{P_\tau - M_{\tau+1}}{M_\tau} \right), \tag{2.2}$$

where $M_{\tau+1}$ represents the midquote after the transaction, used as a proxy for the post-transaction value of the asset. According to Amihud and Mendelson (1980), the realised half-spread represents the compensation of the risk adverse liquidity supplier for bearing the price risk of an order imbalance. It can also be interpreted as the transaction costs net of the adverse selection component. Given private information about the fair asset value, the price reversal may be partial, rather than full. Therefore, movements in the effective half-spread reflect the informational component, i.e. the adverse selection costs due to asymmetric information (Glosten and Milgrom, 1985).

Measures of price impact

The informational, and permanent component of the effective half-spread is measured by the price impact of a transaction. According to Goyenko et al. (2009) and focusing on the changes in the asset value (i.e. midquote) after a transaction, this price impact can be defined as:

$$PI_\tau = D_\tau \left(\frac{M_{\tau+1} - M_\tau}{M_\tau} \right) = \quad EHS_\tau - RHS_\tau. \tag{2.3}$$

The three measures described above can explain the different components of costs a single small transaction. However, liquidity adjusts to the pressure exerted by larger transactions, which are also often executed in multiple transactions (Hasbrouck, 2009; Hendershott and Menkveld, 2014). In order to investigate this aspect of liquidity, in this chapter a second measure of price impact is adopted, which is a slight modification of the one proposed by Hasbrouck (2009) and is drawn from the classical work of Kyle (1985). In contrast to previous literature, however, this measure will be allowed to be time-varying in order to identify changes in the link between trading activity and returns. Furthermore, in estimating this measure the physical volume, rather than its monetary value, is used. This second measure of price impact relies on the theoretical framework by Campbell et al. (1993) and Llorente et al. (2002), who analysed the dynamic relationships between stock returns and traded volumes as well as the role of order flow in the evaluation of future price movements. Since trading volume can allow for the identification of the periods in which either inventory imbalances or informational shocks occur (Llorente et al., 2002), it can provide valuable information about price movements to participants and monitors in the market. This measure is in the spirit of Kyle (1985), who defined liquidity as the response of prices to order flow, and Brennan and Subrahmanyam (1996), who measured market liquidity through price impact, defined as the response of prices to signed order flow. In particular, prices increase in buyer-initiated transactions and decrease in seller-initiated transactions. The impact is increasing with the size of the order flow, which is defined as the difference between buyer-initiated and seller-initiated transactions. Since prices adjust to the information impounded in the order flow gradually, they may not be immediately revised to reflect public information (Hasbrouck, 1991). To overcame the issue of the price adjustment to information over time, the cumulative signed volume over fixed time intervals is considered, thus allowing the evaluation of order flow as a predictor of price changes. Following the proposals by Glosten and Harris (1988) and Hasbrouck (1991), in this study the price impact is identified by the coefficient λ_n that relates transaction price returns to the order flow in the following linear regression model:

$$r_{n,t} = \lambda_n S_{n,t} + u_{n,t}, \tag{2.4}$$

where $r_{n,t}$ is the price return over a fixed time interval t, $t = 1, ..., T$, in the rolling window n and the measure $S_{n,t} = \sum_{\tau} sign(v_{n,t,\tau})\sqrt{v_{n,t,\tau}}$ is the signed square-root of the order flow in the same interval and rolling window. This measure reflects the buying pressure and is computed as the aggregated signed physical volumes $v_{n,t,\tau}$, where τ indexes the transactions in the fixed time interval t and rolling window n; $u_{n,t}$ is the error term. The time-varying coefficient λ_n is estimated by assuming rolling windows of size m over the full sample of size T. Increments between successive rolling windows of one unit of time are assumed, thus leading to $N = T - m + 1$ estimates of the coefficient λ_n over the full sample. The reciprocal of λ_n can be interpreted as a measure of market depth: the lower the value of λ_n, the less sensitive are prices to buying pressure, thus to order flow. Therefore, the present chapter aims to evaluate the pressure exerted by changes in the order flow on returns.

2.4.2 Assessing co-movements between trading activity, volatility and liquidity: A VAR model

Drivers of liquidity in the one-month-ahead NBP forward market are investigated using a VAR framework, which has been used by Chordia et al. (2005a) in the stock market and by Danielsson and Payne (2012) in the foreign-exchange market. The following variables are modelled:

- Order flow, V_t, which is used as a proxy for the trading activity and defined as the cumulative difference between the number of buyer-initiated and seller-initiated transactions (Hasbrouck, 1991; Evans and Lyons, 2002; Payne, 2003) over the 60-minute interval from $t-1$ to t. The trade direction is set according to the Lee and Ready (1991)'s algorithm, as defined above;

- Return volatility, $|R_t|$, which is measured by the absolute log return from the transaction price over the same interval;

- Spread, S_t, which is used as a measure of liquidity and defined by the effective half-spread in absolute basis points, i.e. $S_t = |\ln\left(\frac{P_t}{M_t}\right)|$, where P_t and M_t are the transaction price and midquote recorded at the t^{th} interval, respectively (Goyenko et al., 2009).

Some restrictions are imposed in order to capture the dynamics in trading mechanisms, which are prescribed by the market microstructure theory: information on the asset fair value is aggregated via trading activity, as proxied by the order flow, which subsequently affects volatility; both trading activity and volatility influence liquidity (Kyle, 1985; Glosten and Milgrom, 1985; Easley and O'Hara, 1987). The VAR representation of these theoretical expectations is therefore the following:

$$\begin{aligned}
V_t &= \sum_{i=1}^{p} \alpha_{V,i} V_{t-i} + \sum_{i=1}^{p} \beta_{V,i} |R|_{t-i} + \sum_{i=1}^{p} \gamma_{V,i} S_{t-i} + \varepsilon_{V,t} \\
|R|_t &= \sum_{i=0}^{p} \alpha_{|R|,i} V_{t-i} + \sum_{i=1}^{p} \beta_{|R|,i} |R|_{t-i} + \sum_{i=1}^{p} \gamma_{|R|,i} S_{t-i} + \varepsilon_{|R|,t} \\
S_t &= \sum_{i=0}^{p} \alpha_{S,i} V_{t-i} + \sum_{i=0}^{p} \beta_{S,i} |R|_{t-i} + \sum_{i=1}^{p} \gamma_{S,i} S_{t-i} + \varepsilon_{S,t},
\end{aligned} \tag{2.5}$$

where the innovation terms $\varepsilon_{V,t}$, $\varepsilon_{|R|,t}$, $\varepsilon_{S,t}$ are assumed to be zero mean, independent and identically distributed, and mutually uncorrelated. The order of lag p is selected using the Schwarz Information criterion (SIC). The above model assumes contemporaneous correlations between the variables. In particular, order flow is allowed to contemporaneously affect both return volatility and spread, and return volatility is allowed to influence spread.

The intuition is that high trading activity should reduce liquidity, at least temporarily, and could also move the market price permanently, as suggested in the theory of price formation by Kyle (1985) (Danielsson and Payne, 2012). This theoretical framework is based on evidence from Karpoff (1987), Hasbrouck (1991) and Chordia et al. (2007) that price volatility and liquidity bear a strong relationship with trading activity. According to their findings, trading activity may be driven by portfolio rebalancing decisions of investors in response to changes in the asset valuation (Merton, 1973). Returns affect future trading behaviours. As a consequence, trading activity can be thought to be dependent upon past (absolute) returns (Chordia et al., 2007). Yet, return-dependent trading behaviours, by creating order imbalances and impacting inventory risk, may in turn affect price volatility and liquidity (Stoll, 1978; Odean, 1998; Chordia et al., 2005a). Therefore, both price changes and liquidity are expected to be strongly related to trading activity.

Correlations have been documented in literature between trading activity and price changes (Tauchen and Pitts, 1983; Karpoff, 1987; Ross, 1989; Andersen, 1996; Poon and Granger, 2003; Chordia et al., 2005a; Clements and Todorova, 2014). Correlation have been also documented between liquidity and volatility (Benston and Hagerman, 1974; Stoll, 1978; Copeland and Galai, 1983; Amihud, 2002; Huang et al., 2002; Chordia et al., 2005a) and between liquidity and trading activity (Chordia et al., 2002; Fleming, 2003; Chordia et al., 2005a; Albuquerque et al., 2008). Following Chordia et al. (2005a) and Danielsson and Payne (2012), these correlations are indicated by the imposed restrictions of contemporaneous relationships between volatility and order flow, and between liquidity and order flow and volatility in the VAR specification in Eq. (2.5). Since the measure of trading activity, i.e. order flow, captures the cumulative net buying or selling pressure from traders who demand liquidity over a fixed time interval, it allows also for inferences on the adjustment of both price volatility and liquidity to the information impounded in the trading activity. These restrictions also ensure that the innovation terms of the VAR specification in Eq. (2.5) are uncorrelated. Hence, the innovations in the order flow equation, $\varepsilon_{V,t}$, might reflect unpredictable changes in the trading activity, which can be driven by either inventory rebalancing or information-based trading. Innovations in the volatility equation, $\varepsilon_{|R|,t}$, may capture either transitory and inventory-based effects, or the permanent effects on prices of asymmetric information. Finally, innovations in the spread equation, $\varepsilon_{S,t}$, may mirror transitory and permanent effects of changes in trading activity and price volatility. These effects are recovered by using the moving average (VMA) representation of the VAR in Eq. (2.5):

$$\begin{pmatrix} V_t \\ |R|_t \\ S_t \end{pmatrix} = \begin{pmatrix} A_V(L) & B_V(L) & C_V(L) \\ A_{|R|}(L) & B_{|R|}(L) & C_{|R|}(L) \\ A_S(L) & B_S(L) & C_S(L) \end{pmatrix} \begin{pmatrix} \varepsilon_{V,t} \\ \varepsilon_{|R|,t} \\ \varepsilon_{S,t} \end{pmatrix} \tag{2.6}$$

where, for example, $A_{|R|}(L) = I + A_{|R|,1}L + A_{|R|,2}L^2 + ... + A_{|R|,k}L^k$ and $L^k\varepsilon_{|R|,t} = \varepsilon_{|R|,t-k}$ represents the lag operator. Under the assumption of mutually uncorrelated innovation terms, the VMA representation gives the impulse responses implied by the VAR. Consequently, the lag polynomial $A_{|R|}(L)$ represents the cumulative effect of a standard error innovation in the order flow on the return volatility at a k-period horizon. Similarly, the cumulative effects of a standard error innovation in the order flow and volatility on the spread are given by the lag polynomials $A_S(L)$ and $B_S(L)$, respectively. The impulse response functions are estimated through Monte Carlo simulations.

The VAR specification above assumes that the cross-correlations are time-invariant. Nonetheless, in the one-month-ahead NBP forward market correlations between variables may have changed in response to a different regulatory framework and market conditions (e.g. business cycles). Therefore, the time-varying rolling approach used for the measure of price impact λ_n is here adopted. That is, the coefficients αs, βs, γs of the VAR model in Eq. (2.5) are estimated using rolling windows of size m and changes in those coefficients are assessed via plots of their estimates over time.

2.4.3 Assessing the implication of REMIT: An event analysis

As mentioned above, the compulsory report of transactions in the wholesale energy markets, which is prescribed by REMIT, has been effective from 7 October 2015. Nonetheless, it is expected that trading behaviour and informational content in the OTC market would have progressively adapted to meet the new regulatory framework. Hence, the potential implications of higher transparency for liquidity are investigated assuming the entering into force of REMIT on 28 December 2011, which corresponds to the 20^{th} day after the publication of REMIT in the Official Journal of the European Union on 8 December 2011 (Article 22). An event analysis procedure, which has been inspired by Hedge and McDermott (2003), is used.

The day of the entering into force of REMIT is considered to be at time $t = 0$. The period in the sample before the entering into force of REMIT identifies the Pre-REMIT time window. The Post-REMIT time window is defined by the period following the entering into force of REMIT. Pre- and ost-REMIT measures of spread and price impact, as defined above, are computed over the two time windows; t-tests and non-parametric sign tests of the mean and median values, respectively, are used to test for the equality of the effective and realised half-spreads, and the first measure of price impact in the pre- and post-event sub-samples. One-tail F-tests for equal variances between the two sub-samples are also performed. Chow (1960)'s test for known structural breaks is used to investigate changes in the price impact measure λ_n after REMIT. T-tests, χ^2-statistics and the Chow's tests are used in the VAR specification in Eq.(2.5) to identify changes in the correlations between the variables after REMIT.

Assessing the sensitivity to REMIT start date: A time-trend intervention analysis

In addition to the analysis described above, a time-trend intervention is performed to evaluate the sensitivity of the results to the start date of REMIT. This event analysis assumes a progressive increase in the intensity of the impact of the regulation since its entering into force.

In the case of the liquidity measures in Eq (2.1)-(2.3), an intervention variable IT_τ, τ=$0, ..., T$ is assumed, which is zero from the beginning of the sample to the start of the intervention on 28 December 2011. During the intervention period, starting at the first available trading day following the coming into force of REMIT, i.e. on 29 December

2011, the variable assumes values $1, 2, 3, ..., N$, where N is the last observation of the intervention period. Therefore, for each liquidity measure, the following regression model is estimated:

$$y_\tau = \alpha + \beta IT_\tau + \epsilon_\tau, \tag{2.7}$$

where is y_τ=$EHS_\tau, RHS_\tau, PI_\tau$ in Eq (2.1)-(2.3) and ϵ_τ the error term.

When the price impact measure λ in Eq. (2.4) and the VAR model in Eq. (2.5) are considered, the analysis is performed by assuming an intervention dummy ID_t, t=0, ..., T, which is zero from the beginning of the sample to the start date for REMIT and one during the intervention period. The sensitivity of the results to the entering into force of REMIT is therefore investigated by defining the intervention period according to different starting dates with increases of one week over a three-month interval, from the first available trading day following REMIT, on 29 December 2011, to 28 March 2012. The following model for the measure λ in Eq. (2.4) is therefore estimated:

$$r_t = \lambda S_t + \delta S_t ID_t + u_t, \tag{2.8}$$

where the coefficient δ measures the sensitivity of the relationship between transaction price returns and order flow to the implementation date of the new regulatory course. In a similar vein, the sensitivity of the correlations between order flow, volatility and spread in Eq. (2.5) to the progressive adaptation to REMIT is investigated by estimating the following VAR model:

$$\begin{aligned}
V_t &= \sum_{i=1}^{p} \alpha_{V,i} V_{t-i} + \sum_{i=1}^{p} \beta_{V,i} |R|_{t-i} + \sum_{i=1}^{p} \gamma_{V,i} S_{t-i} + \varepsilon_{V,t} \\
|R|_t &= \phi V_t ID_t + \sum_{i=0}^{p} \alpha_{|R|,i} V_{t-i} + \sum_{i=1}^{p} \beta_{|R|,i} |R|_{t-i} + \sum_{i=1}^{p} \gamma_{|R|,i} S_{t-i} + \varepsilon_{|R|,t} \\
S_t &= \varphi V_t ID_t + \psi |R|_t ID_t + \sum_{i=0}^{p} \alpha_{S,i} V_{t-i} + \sum_{i=0}^{p} \beta_{S,i} |R|_{t-i} + \sum_{i=1}^{p} \gamma_{S,i} S_{t-i} + \varepsilon_{S,t},
\end{aligned} \tag{2.9}$$

where the coefficient ϕ allows to infer the sensitivity of the correlation between volatility and order flow to the start date for REMIT; similarly, the coefficients φ and ψ measure the responsiveness of the correlation between spread and order flow and volatility, respectively, to REMIT implementation.

2.4.4 Deseasonalising and detrending variables

The natural gas prices are characterised by seasonalities and trends (Mu, 2007), which have been also observed in Figure 2.1. Therefore, it is important to ensure that predictable movements in the natural gas market activity that may affect the liquidity measures in Eq. (2.1)-(2.4) and the dependent variables in Eq. (2.5) in a similar way are removed. The focus of the analysis is thus on the irregular component of the series (the residuals). Following Chordia et al. (2005b), each raw time series y is regressed on a set of adjustment variables, X, which in this chapter are: 11 month-of-the-year dummies (February - December); 4 day-of-the-week dummies (Tuesday-Friday); (8 hour-of-day dummies, 8.00-15.00;) a time-trend, i.e.:

$$y = X\beta + u. \tag{2.10}$$

In order to standardise the residual series from the above regression, $\hat{u}$, a second equation is estimated:

$$log(\hat{u}^2) = X\gamma + v. \tag{2.11}$$

Finally, the seasonally adjusted time series to be analysed is:

$$\tilde{y} = a + b\left(\frac{\hat{u}}{exp(X\hat{\gamma}/2)}\right), \tag{2.12}$$

where a and b are set so that raw and adjusted sample means and variances are the same. This transformation makes the units of measurement of the original and adjusted time series the same, therefore facilitating the interpretation of the parameter estimates.

2.5 Data

This chapter analyses a unique database, which records transactions and quotes of the NBP forward contracts over the period from 7 May, 2010 to 29 December, 2014, and includes when REMIT came into force. The data were made available by Tullett Prebon, one of the world's leading inter-dealer brokers, which managed a third of the total OTC market for the NBP at that time. Since Tullett Prebon was only one of the inter-dealer brokers operating in the OTC market for the natural gas (with ICAP Energy and Marex Spectron being the other leading inter-dealer brokers), a full picture of the overall liquidity dynamics in the NBP forward cannot be provided as data of one particular trading venue are analysed. Nonetheless, the analysis is highly informative with respect to the objective of this chapter. In the following subsections the database is described, along with its cleaning and resampling procedures, which were required for the analysis.

2.5.1 Database

Two data sets were considered. The first records tick-by-tick indicative quotes (best bid and best ask); the second records tick-by-tick transaction prices and volumes. The data set of the indicative quotes has 1,837,337 data lines. Each line contains 5 fields detailing product (i.e. the contract tenor), Greenwich Mean Time (GMT) timestamp with a one second accuracy, London local timestamp with a one second accuracy, and the best ask and best bid prices, expressed in GBpence/therm.

The data set containing transactions has 543,649 data lines and 8 fields. The first field reports the status ("recorded", "removed", "cancelled") of each transaction in the transaction trace recording system. The second and third fields indicate the timestamps that refer to the submission and execution of each transaction, respectively. Both the timestamps are in GMT time with a one second accuracy. The fourth and fifth fields include the transaction price and the corresponding traded volume. Volumes are expressed in lots of 1,000 of therm per day. The sixth field identifies the type of contract, i.e. if forward or basis swap; the location, i.e. NBP or Zeebrugge, in case of basis swap; the clearing venue (when the transaction is cleared through the ICE platform instead of bilaterally); the transaction price unit (Pence/therm, euro/megawatthour, or basis points); and the tenor.

The data-lines corresponding to the one-month-ahead entries, for the delivery over the next month, are extracted from both data sets, since this maturity can be used as a proxy for the spot price (e.g. Geman, 2007). This results in 461,663 observations. To account for the discrete nature of the tick-by-tick data and prepare the data set for the empirical analysis, a step-by-step cleaning procedure is adopted, which identifies and discards observations that are not of interest (e.g. indexes and basis swaps), errors and outliers. This procedure is described below.

Data cleaning

The cleaning procedure is based on Brownlees and Gallo (2006) and Barndorff-Nielsen et al. (2009). Entries with bid, ask or transaction price equal to zero, and entries with negative spreads are discarded. Holidays and weekends are deleted and the trading window 7:00-17:00 (GMT) is considered. Simultaneous quotes and transaction prices are aggregated by using as single entry the median quotes and the median price, respectively; the corresponding simultaneous volumes and transaction counts are aggregated by their respective totals. Aggregation is need as high-frequency models dealing with tick-by-tick data usually require one observation per timestamp.

Following Barndorff-Nielsen et al. (2009), outliers are detected via a non-parametric distance-based approach. Entries for which the bid-ask spread is greater than 10 times the median spread of that day are discarded. Similarly, entries are deleted if the midquote deviates by more than 10 mean absolute deviations from the median midquote on that day. Observations are deleted when the transaction price deviates by more than 10 times the mean of the absolute deviations from the daily median midquote. This last rule smooths the trade data using quotes and is applied by comparing each transaction price to the prevailing midquote.

The data cleaning procedure is summarised in Table 2.1. Panel a and Panel b report the number of quotes and transactions available after each step, respectively. Limiting trading window refers to the time 7:00-17:00, after removing holidays and weekends. In Panel b, transactions referring to OTC NBP forwards are extracted. Simultaneous quotes and transactions are thus aggregated. Outliers are detected as described above. They are mainly observed at the opening and closing of the trading, during the intervals 7.00-8.00 and 16.00-17.00, thus suggesting some adjustment to overnight information and daytime effects in the trading activity exhibiting excess of variability. Similar pattern has been also found in financial markets (e.g. Boudt et al., 2011; Boffelli and Urga, 2015). Data cleaning results in discarding 1.4% of quotes and 2.7% of transactions, 62% and 57% of which, respectively, is observed after REMIT. On average, 235.97 quotes and 66.79 transactions are recorded each day (with a standard deviation of 108.58 and 31.68, respectively). Together the cleaning and subsequent alignment of each transaction to the prevailing midquote results in 78,019 observations that are recorded at trading time over the period 7 May 2010 - 29 December 2014, totalling 1,170 trading days.

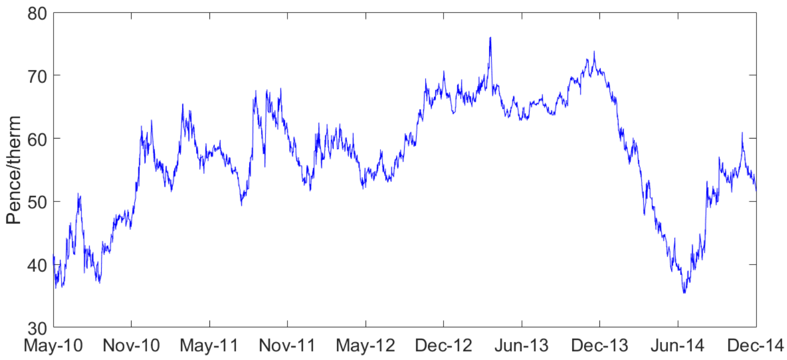
Table 2.1: Summary of the data cleaning procedure

Cleaning step	Number of observations
Panel a: Quotes	
No. of ticks	350,889
Limiting trading window	349,093
Aggregating simultaneous quotes	280,001
Deleting entries with negative spread	279,999
Deleting outliers (%)	276, 090 (1.4)
No. Quotes per day: Mean (St.Dev.)	235.97 (108.58)
Panel b: Transactions	
No. of ticks	110,774
Limiting trading window	106,701
OTC NBP forwards	93,503
Deleting removed or corrected entries	90,224
Aggregating simultaneous trades	80,167
Deleting outliers (%)	78,019 (2.7)
No. Transactions per day: Mean (St.Dev.)	66.79 (31.68)

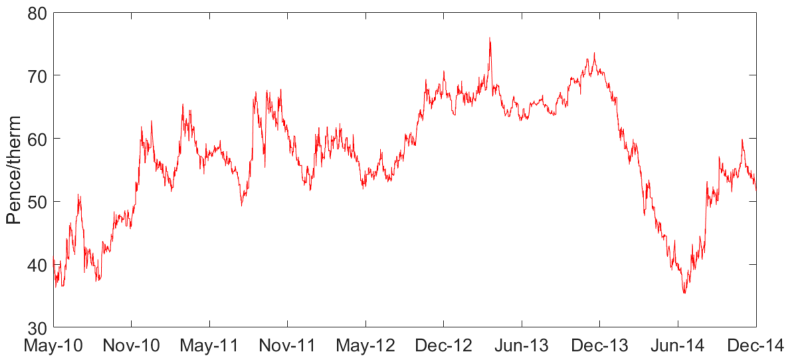
NBP transaction price and midquote series, after the cleaning procedure, are shown in Figure 2.2. The figure highlights not only a doubling of prices and midquotes (Figure 2.2 (a)-(b)) between May 2010 and December 2013, but also a significant drop since January

2014. The increase is more pronounced in the period from the second-half of 2012 to the first-quarter of 2013 and can be explained by natural gas demand/supply imbalances in the UK and Continental Europe, which were due to a Norwegian supply disruption, low storage level and sustained cold weather in the UK that was mainly evident in March 2013 (European Commission, 2013; Timera-Energy, 2013). Subsequently, the slump in international coal prices and the increasing availability of LNG from the international gas market are likely to have led lower one-month-ahead NBP forward prices, as observed since the second-half of 2013.

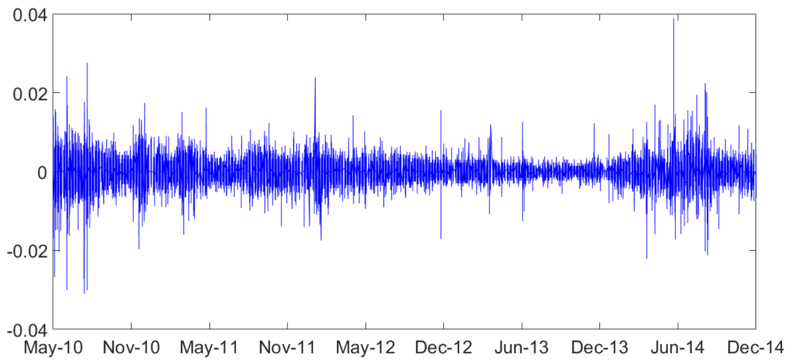
Returns computed from the transaction price and midquote series are shown in Figure 2.2 (c)-(d) and suggest volatility clustering, excess kurtosis and heteroscedasticity. These characteristics are typically observed in financial time series and justify the adoption of measures from the financial literature. A decrease in the volatility of price returns can also be observed in Figure 2.2 (c). The plots also indicate higher volatility in the midquote returns relative to the price returns, which could be due to the fact that midquotes are computed from the ask and bid quotes that are based on trading orders and expressions of interest and thus may differ from actual prices. It is noteworthy that persistent disparities between quotes and transaction prices within OTC markets have been also observed in the financial literature, in particular in bond markets (Froot, 2008; Zhu, 2012).



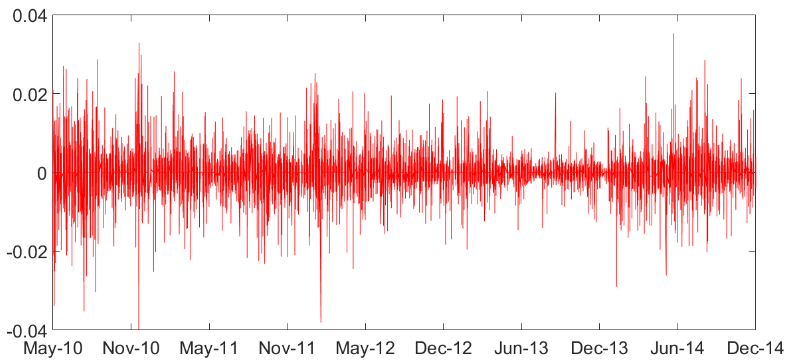
(a) Transaction prices



(b) Midquotes



(c) Transaction price returns



(d) Midquote returns

Figure 2.2: One-month ahead NBP transaction and midquote prices and returns

Resampling procedure

The data are resampled at regularly spaced time-intervals. According to Foucault et al. (2013), regular time intervals are required to ensure that prices have adjusted to the information content of the cumulative transactions over time. Similarly to Zhang et al. (2005), the trading window is split in fixed-time intervals. For each time interval, the following information is extracted: the end-of-interval price; the end-of-interval quotes; the end-of-interval volume; the total trading volume over the interval; the total trade size over the interval; the total number of transactions over the interval. When a time interval does not contain observations, the most recent recorded observation is used. Finally, in the spirit of Boffelli and Urga (2015), the first record of each day is excluded from the sample, because it could reflect the adjustment to the overnight information and thus exhibit an excessive variability when compared to the other observations in the same day. This resampling procedure is performed at different frequencies: 5, 15, 30, and 60 minutes. The aim is to identify the best frequency to be used in the empirical analysis, which should minimise volatility clustering, kurtosis and autocorrelation in the midquote and transaction price return series.

Descriptive statistics of the raw quote and transaction series and of the time series resampled at different frequencies (5, 15, 30 and 60 minutes) are reported in Table 2.2. The number of observations (column two) and observations per day (column three) are shown in the top of Panel a, along with the average best ask and best bid quotes, in pence/therm, and the corresponding midquote (columns four, five and six). Standard errors are reported in brackets. The first (M_{25}) and third (M_{75}) interquartile of the midquote series are shown in column seven and eight, respectively. In the bottom of Panel a, the distribution of the midquote return series is summarised. The first four moments are shown in columns two to five (Mean, Std.Dev., Skewness and Kurtosis, respectively); for clarity, means and standard deviations have been multiplied by 10^3. The first lag of the autocorrelation function, ρ_1, is shown in column six. Columns seven and eight report, respectively, the Ljung-Box statistics for the null hypothesis of serial independence and the ARCH test for the null hypothesis of homoscedasticity, which have been computed at the 50^{th} order of lags and account for a time window spanning from one day (raw data) to one week (Monday-Friday, data resampled at 60-minute frequency).

In Panel (b) of Table 2.2, the descriptive statistics of the transaction series (top) and the distribution of the transaction price returns (bottom) are shown. Number of observations and observations per day are reported in columns two and three, respectively. Volume (1,000 therm/day), size (million £) and transaction price (pence/therm) are shown in columns three to five respectively; their standard errors are reported in brackets. Columns seven and eight show the first (P_{25}) and third (P_{75}) interquartile of the price series. The first four moments of the price return series are reported in columns two to five, after multiplying the mean and standard deviation values by 10^3. The first lag of the autocorrelation function, the Ljung-Box statistics and the ARCH tests are shown in columns six to eight.

Table 2.2: Descriptive statistics of raw and resampled quotes and transactions at different frequencies

Panel a: Quotes	Obs.	Obs. p.d.	Ask	Bid	Miquote	M_{25}	M_{75}
Raw data	78,019	66.80	57.43 (8.65)	57.33 (8.66)	57.38 (8.66)	53.05	65.15
5 mins	141,570	121	57.07 (8.92)	56.97 (8.93)	57.02 (8.93)	52.60	64.75
15 mins	47,970	41	57.06 (8.92)	56.96 (8.93)	57.01 (8.93)	52.60	64.75
30 mins	24,570	21	57.06 (8.92)	56.96 (8.93)	57.02 (8.93)	52.61	64.75
60 mins	12,870	11	57.06 (8.92)	56.96 (8.93)	57.01 (8.93)	52.64	64.75
Midquote returns	Mean	Std. Dev.	Skewness	Kurtosis	ρ_1	Ljung-Box(50)	ARCH(50)
Raw data	-0.002	1.713	-0.217	70.0	0.008	124.9***	348.6***
5 mins	0.002	1.715	13.80	1580	0.005	64.21*	1.989
15 mins	0.005	2.983	7.726	502.7	0.004	72.49***	6.901
30 mins	0.010	4.218	5.515	252.4	0.013	68.62**	10.34
60 mins	0.020	5.993	3.789	125.2	0.026**	99.17***	14.88
Panel b: Transactions	Obs.	Obs. p.d.	Volume	Size	Price	P_{25}	P_{75}
Raw data	78,019	66.79	40.07 (93.06)	0.70 (1.72)	57.38 (8.66)	53.05	65.15
5 mins	141,570	121	52.37 (147.8)	0.91 (2.64)	57.01 (8.93)	52.60	64.75
15 mins	47,970	41	52.27 (145.47)	0.91 (2.60)	57.01 (8.93)	52.60	64.75
30 mins	24,570	21	52.44 (143.36)	0.91 (2.57)	57.01 (8.93)	52.60	64.75
60 mins	12,870	11	53.39 (150.0)	0.93 (2.69)	57.01 (8.93)	52.60	64.75
Price Returns	Mean	Std. Dev.	Skewness	Kurtosis	ρ_1	Ljung-Box(50)	ARCH(50)
Raw data	-0.002	1.590	-0.202	34.3	-0.017	154.6***	933.40***
5 mins	0.001	1.775	10.98	1353	0.008	55.10	0.906
15 mins	0.004	3.093	6.438	457.0	0.008	61.08	3.346
30 mins	0.008	4.382	4.516	228.1	-0.001	71.85***	6.771
60 mins	0.015	6.151	3.070	117.1	0.004	81.92***	8.817

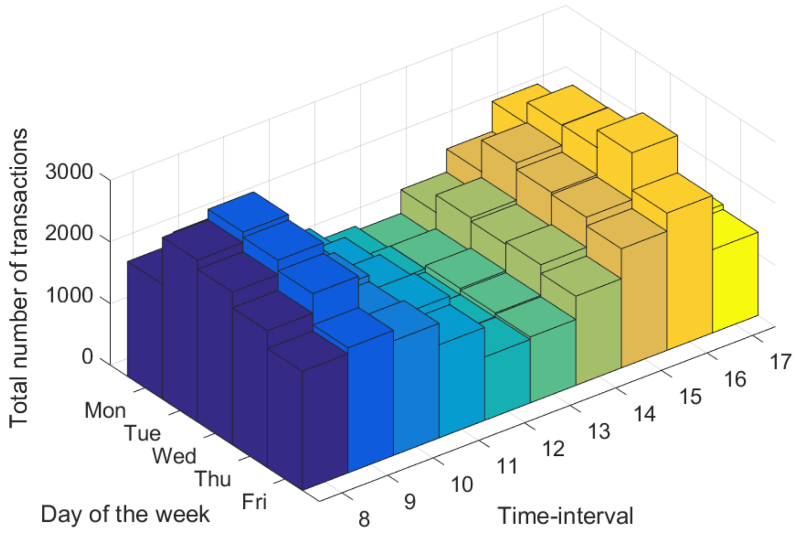
Note: ***, ** and * denote significance at 1%, 5% and 10%, respectively.

When compared to the raw series, resampled midquote and price return series show higher kurtosis, which however reduces with the resampling frequency. That is, higher kurtosis is observed in the data resampled at 5-minute frequency (1,580 and 1,353, in the midquote and price return series, respectively), when 121 observations per day are recorded, compared to the data resampled at 60-minute frequency (125.2 and 117.1), with 11 recorded observations per day. This difference in kurtosis might be due to low trading frequency in the NBP forward market. Based on the raw series, 66.8 transactions are recorded, on average, each day. Resampling procedure by replicating observations may amplify rather than filter the microstructure noise in the time series at higher frequencies when data are unavailable in the interval, and this may increase leptokurtosis. A similar argument may also apply to the skewness of the time series.

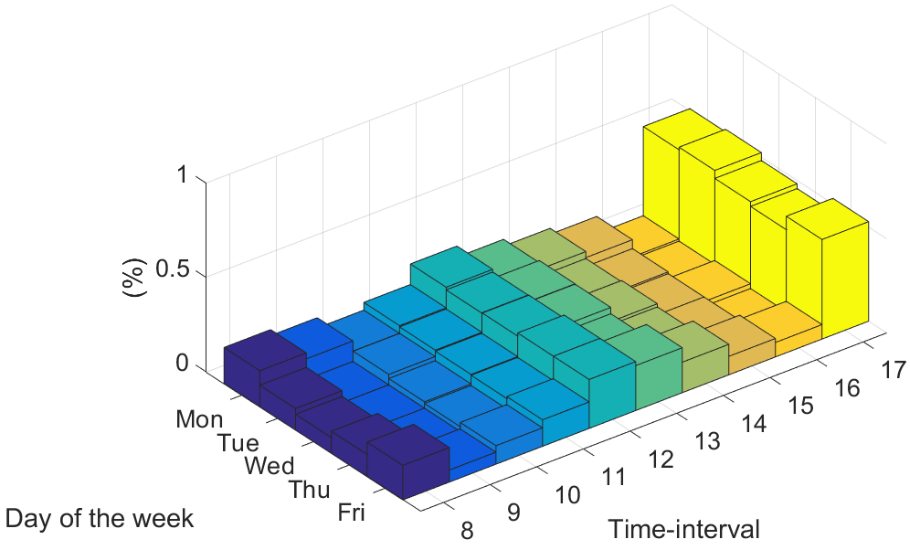
ARCH effects are rejected (at 1% significance level) when the resampling procedure is adopted, while the returns remain serially correlated after resampling, except when 5- and 15-minute frequencies are considered. Therefore, the focus in subsequent analysis is on 60-minute resampling, because this frequency minimises leptokurtosis and asymmetric effects. This choice results in a sample of size T=12,870 observations, corresponding to 11 observations per day.

2.5.2 Preliminary data analysis

The trading activity in the one-month-ahead NBP forward market is summarised in Figure 2.3 and Figure 2.4. The total number of transactions by day of the week (Monday-Friday) and over the 60-minute intervals is depicted in Figure 2.3 (a). There is high concentration of trading as the market opens (8:00-10:00) and preceding the day's closure (15:00-16:00). With the intent of investigating trading frequency in the one-month-ahead NBP forward market, the number of times where no transactions are recorded in the 60-minute intervals was considered, by day of the week, and its frequency (in percentage) was computed (Figure 2.3 (b)). On average, this frequency is observed to be of 49% between 16:00 and 17:00, i.e. at the end of the business day. This value increases to 54% on Fridays. Overall, this finding tallies with evidence from the cleaning procedure, suggesting high frequency of outliers at the opening and closing hours of the trading day. Consequently, the subsequent analysis is focused on the trading window 8:00 to 16:00.



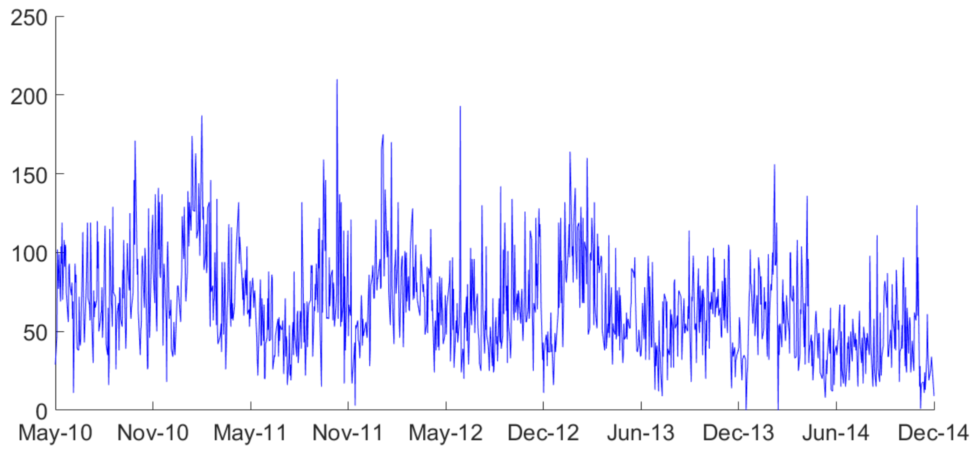
(a) Number of transactions by day of the week



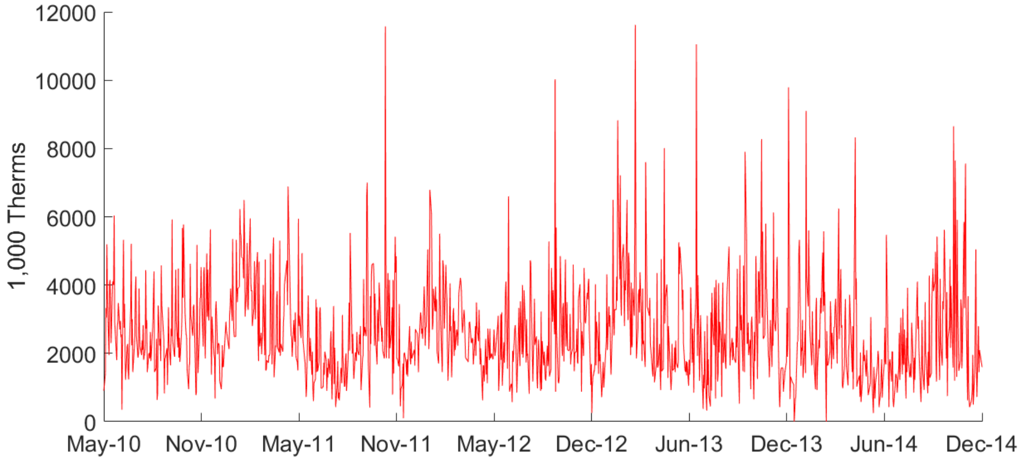
(b) Frequency of no trading

Figure 2.3: Number of transactions and no trading frequency

The daily number of transactions over the full sample (Figure 2.4 (a)) indicates decreasing trading activity since May 2013. A seasonal pattern is also observed: daily transactions are greater from September to November and during the winter (January to March). This seasonality is likely to reflect the weather-dependence of the demand for natural gas. Figure 2.4 (b) shows the daily trading volume, where its increasing variance can be observed, most noticeably from May 2013 onwards. Together charts (a) and (b) suggest growing physical trade size over the period, which may be driven by changes in trading behaviours and market composition.



(a) Daily number of transactions



(b) Daily trading volume

Figure 2.4: Daily trading activity

Descriptive statistics of daily transactions and trading volumes are reported in Table 2.3. The number of observations is shown in column two. The first four moments (Mean, Std.Dev., Skewness and Kurtosis) are shown in columns three to six. The first lag of the autocorrelation function, ρ_1, is shown in column seven. Columns eight and nine report, respectively, the Ljung-Box statistics and the ARCH tests, computed at the 20^{th} order of lags, which accounts for a time window spanning one month. The variables are characterised by asymmetric and leptokurtic distributions, as well as positive first-order autocorrelation. Serial correlation and ARCH effects are not rejected at 1% significance level.

Table 2.3: Descriptive statistics of the daily number of transactions and trading volumes

	Obs.	Mean	Std. Dev.	Skewness	Kurtosis	ρ_1	Ljung-Box (20)	ARCH(20)
Daily transactions	1,170	65.99	31.20	0.799	3.856	0.468***	1907***	306.4***
Daily volume	1,170	2622	1450	1.554	7.544	0.248***	333.1***	63.38***

Note:***, ** and * denote significance at 1%, 5% and 10%, respectively.

As predicted by the market microstructure theory, both trading activity and return volatility contribute to liquidity. Therefore, given the trends and seasonalities observed above, movements in liquidity of the one-month-ahead NBP forward market are investigated. Results are presented in the next section.

2.6 Empirical Findings

2.6.1 Liquidity in the NBP

Descriptive statistics of the daily effective half-spread and its two components, the daily average percentage realised half-spread and price impact, are presented in Table 2.4. Daily averages were computed as time-weighted average of the intraday measures, through multiplying each of them by the relative time it was observed during the day. For each measure, mean, standard deviation (St. Dev.), lower quartile (Q_{25}), median and upper quartile (Q_{75}) from the empirical distributions are shown (columns two to six). The estimated autocorrelation at lag one is also given (column seven). The measures are characterised by having asymmetric distribution and positive first-order autocorrelation. On average, daily transaction costs in the one-month-ahead NBP forward market are 0.312%, which are split between a transitory and non-informational component of 0.171%, given by the percentage realised half-spread, and a permanent and informational component of 0.141%, given by the price impact measure. That is, on average, inventory costs represent 55% of the transaction costs and the remaining 45% is due to asymmetric information. The t-test for equal mean values between realised half-spread and price impact is significant at 5% significance level. Similarly, non-parametric sign tests for the equality between the respective medians and interquartile statistics are significant at 5% significance level.

Table 2.4: Descriptive statistics of the daily liquidity measures

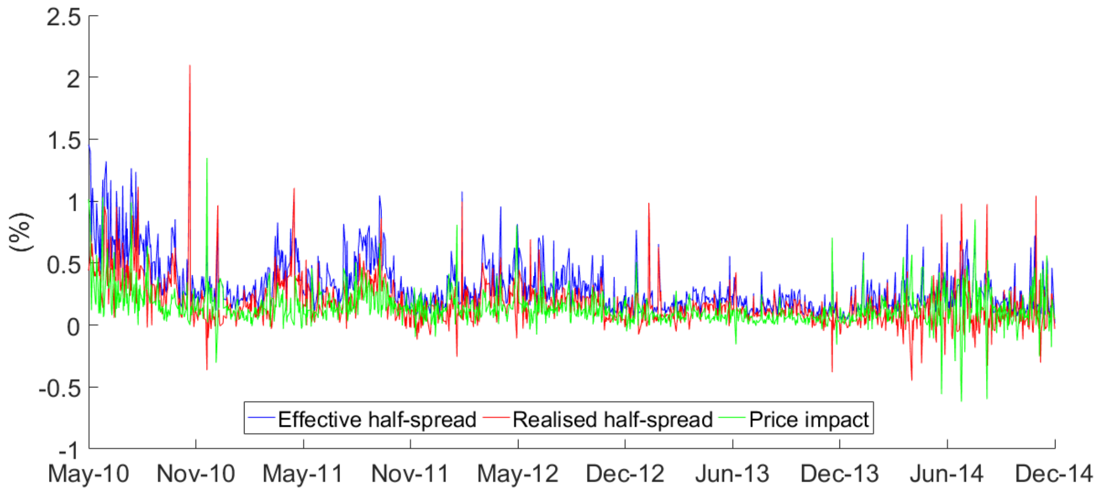
	Mean	St. Dev.	Q^{25}	Median	Q^{75}	ρ_1
Effective half-spread	0.312	0.223	0.162	0.242	0.391	0.595***
Realised half-spread	0.171	0.186	0.062	0.130	0.243	0.395**
Price Impact	0.140	0.144	0.062	0.114	0.184	0.272**

Note:***, ** and * denote significance at 1%, 5% and 10%, respectively.

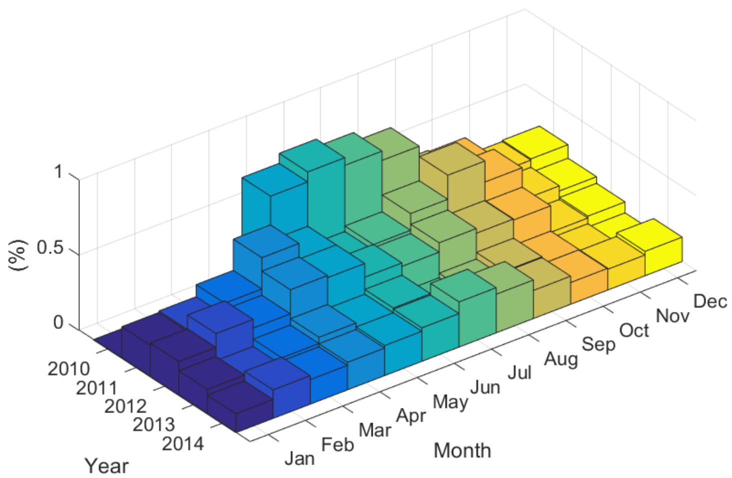
Overall, there are differences between the distributions of the realised half-spread and price impact measures. This implies distinct behaviours of the different dimensions of liquidity in the one-month-ahead NBP forward market.

The time-weighted daily average liquidity measures are depicted in Figure 2.5 (a). Sudden one-day changes are observed, which mainly occur during the contract roll-over, between the last trading day of one month, when the contract expires, and the first trading day of the following month, when the new contract begins to be traded (e.g. 29/10-01/11/2013). Therefore, some intra-month effects are suggested as the contract approaches delivery. Nonetheless, the focus of this study in on long-term dynamics of one-month-ahead NBP forward market liquidity.

Monthly medians of the liquidity measures, by year, are depicted in Figure 2.5 (b)-(d) and highlight the seasonal behaviour of these measures: lower transaction costs are observed from October to March, which resembles the observed pattern of trading activity and suggest that liquidity increases during the winter season when trading activity is higher. Therefore, the adoption of adjustment procedures is here justified.

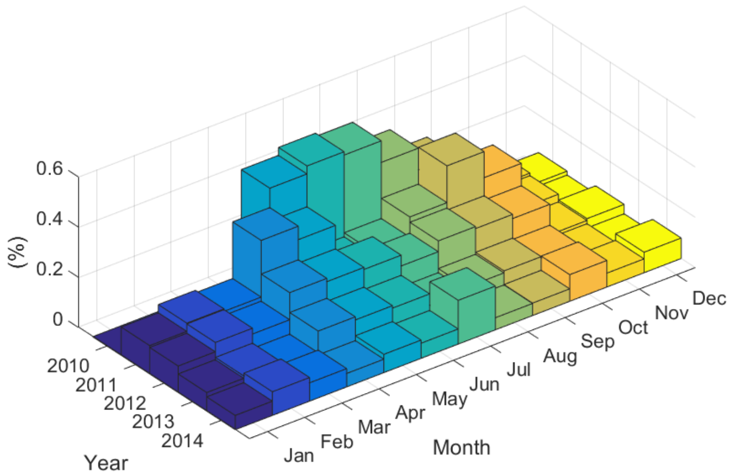


(a) Daily time-weighted averages

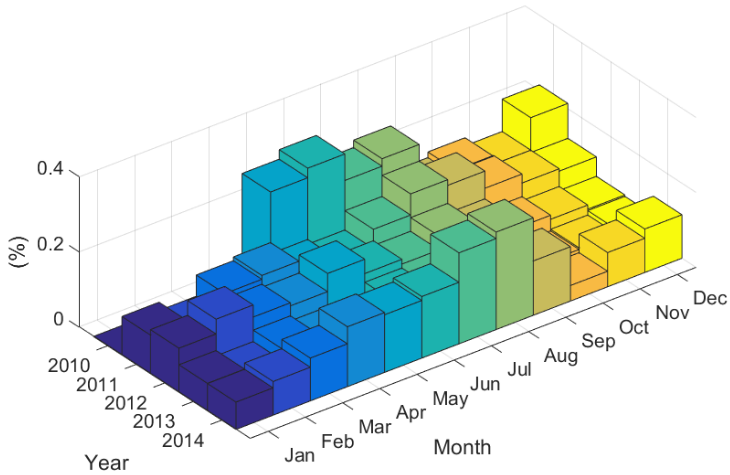


(b) Effective half-spread medians

Figure 2.5: Liquidity measure



(c) Realised half-spread medians



(d) Price impact medians

Figure 2.5: Liquidity measure (Cont.)

The implementation of the adjustment procedure described in Eq. (2.10)-(2.12) is summarised in Table 2.5. The table presents the coefficients from the regressions of the daily liquidity measures on 11 month-of-the-year dummies (February - December); 4 day-of-the-week dummies (Tuesday-Friday); a time-trend over a sample size of T=1,170 observations. Robust standard errors are based on Newey-West estimator (Newey and West, 1987). According to the three measures and their standard errors, tends to be higher during the winter and lower during the summer, thus supporting evidence from Figure 2.5. Furthermore, liquidity is lower on Mondays relative to other trading days, which is in line with some empirical evidence from financial markets (e.g. Chordia et al., 2005b). Additionally, a significant negative trend is found in the time series, which is shown in the last row of Table 2.5 and implies a progressive increase in the one-month-ahead NBP forward market liquidity throughout the sample.

Table 2.5: Parameter estimates of the adjustment regressions of the daily liquidity measures

		Effective half-spread			Realised half-spread			Price impact		
		Coeff.	Std.Err.	t-Stat	Coeff.	Std.Err.	t-Stat	Coeff.	Std.Err.	t-Stat
Intercept		0.444***	0.024	18.16	0.248***	0.024	10.45	0.196***	0.015	12.96
Month	Feb	0.036	0.023	1.540	0.035	0.023	1.528	-0.0005	0.014	-0.035
	Mar	0.043**	0.021	1.994	0.019	0.021	0.906	0.021*	0.012	1.717
	Apr	0.147***	0.023	6.273	0.094***	0.022	4.282	0.050***	0.015	3.230
	May	0.193***	0.027	6.935	0.121***	0.022	5.340	0.070***	0.020	3.581
	Jun	0.179***	0.027	6.548	0.119***	0.025	4.635	0.057***	0.019	3.060
	Jul	0.168***	0.027	6.107	0.114***	0.024	4.640	0.051***	0.019	2.682
	Aug	0.176***	0.022	7.672	0.086***	0.021	4.099	0.091***	0.017	5.487
	Sep	0.146***	0.022	6.663	0.104***	0.021	4.964	0.039***	0.015	2.566
	Oct	0.108***	0.021	5.010	0.093***	0.020	4.594	0.012	0.012	1.045
	Nov	0.028	0.027	1.029	0.008	0.028	0.296	0.020	0.013	1.565
	Dec	0.029	0.024	1.201	-0.016	0.024	-0.660	0.037	0.023	1.625
Day	Tue	-0.075***	0.019	-3.885	-0.031*	0.017	-1.820	-0.043***	0.014	-2.997
	Wed	-0.077***	0.019	-3.919	-0.031*	0.017	-1.733	-0.047***	0.014	-3.250
	Thu	-0.079***	0.018	-4.323	-0.030*	0.016	-1.846	-0.050***	0.013	-3.736
	Fri	-0.061***	0.019	-3.136	-0.013	0.017	-0.767	-0.049***	0.015	-3.259
Trend		-0.0003***	0.000	-16.34	-0.0002***	0.00002	-11.94	-0.0001***	0.00001	-6.653

Note:***, **, * denote 1%, 5% and 10% significance level, respectively.

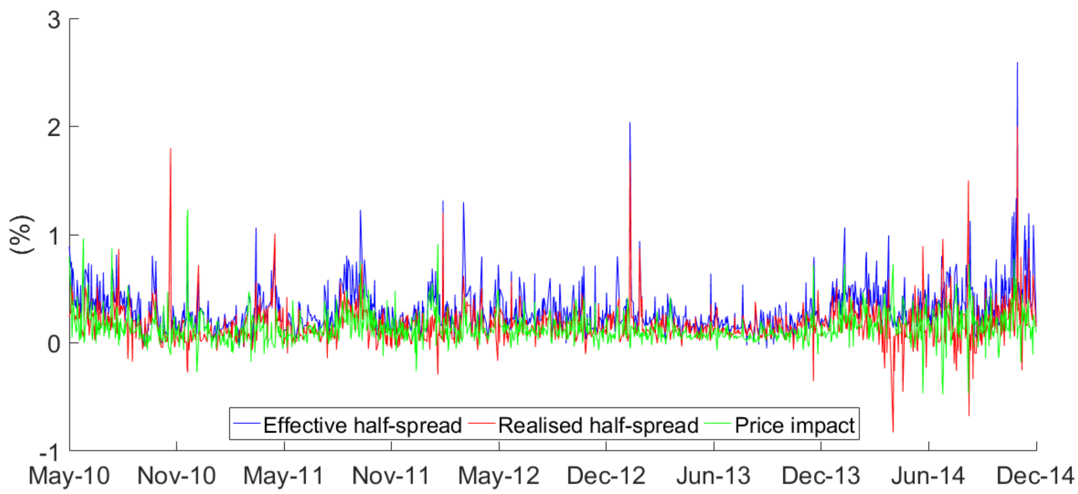
Descriptive statistics of the seasonally adjusted daily liquidity measures are presented in Table 2.6. Lower asymmetry in the empirical distributions of the effective and realised half-spread measures can be observed relative to the non-adjusted series, as shown by their means and medians (columns two and five). By contrast, higher asymmetry in the distribution of the adjusted price impact can be noticed when compared with the non-adjusted measure.

Table 2.6: Descriptive statistics of the seasonally adjusted daily liquidity measures

	Mean	St. Dev.	Q^{25}	Median	Q^{75}	ρ_1
Effective half-spread	0.312	0.223	0.170	0.259	0.395	0.421***
Realised half-spread	0.171	0.186	0.076	0.143	0.240	0.182***
Price impact	0.141	0.145	0.057	0.109	0.196	0.224***

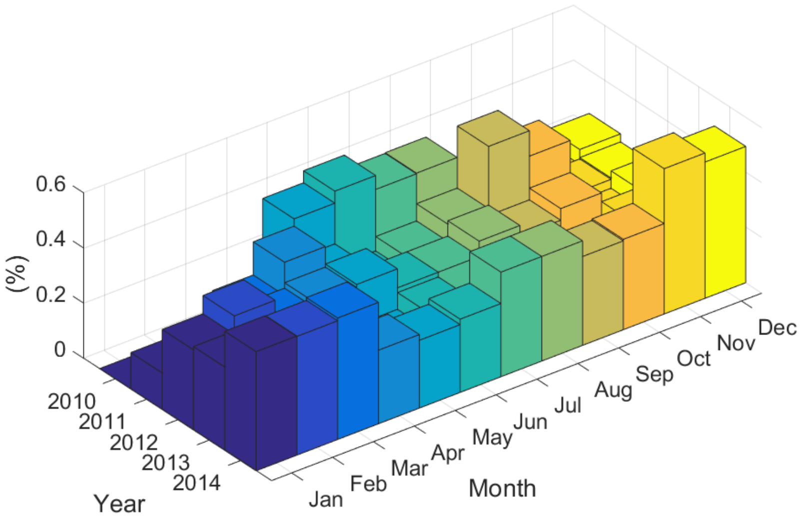
Note:***, ** and * denote significance at 1%, 5% and 10%, respectively.

The deseasonalised and detrended liquidity measures are shown in Figure 2.6. Overall, they suggest an increase in the transaction costs during 2014. Furthermore, liquidity in the one-month-ahead NBP forward market becomes more volatile in 2014 relative to the previous period. In comparison with the unadjusted time series (Figure 2.5), the adjusted measures are higher during the winter, as indicated by their medians (Figure 2.6 (b)-(d)). This pattern is clearer in 2013 and 2014, particularly when the effective and realised half-spread measures are considered (Figure 2.6 (b)-(c)).

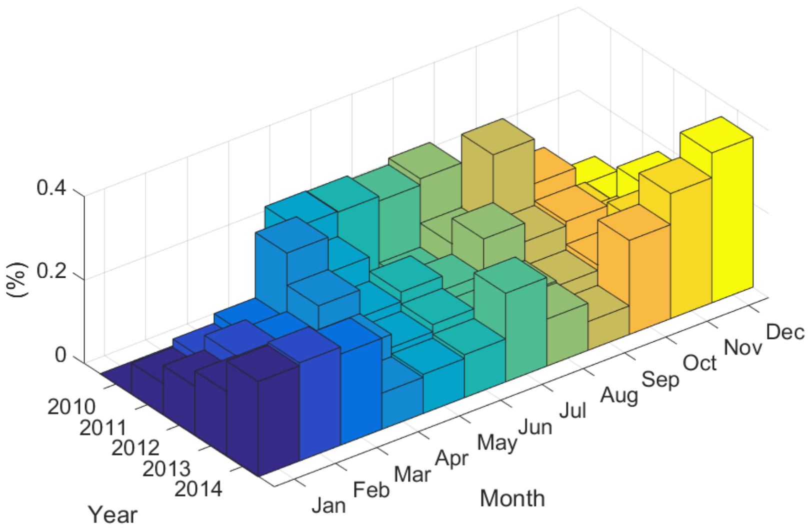


(a) Daily time-weighted averages

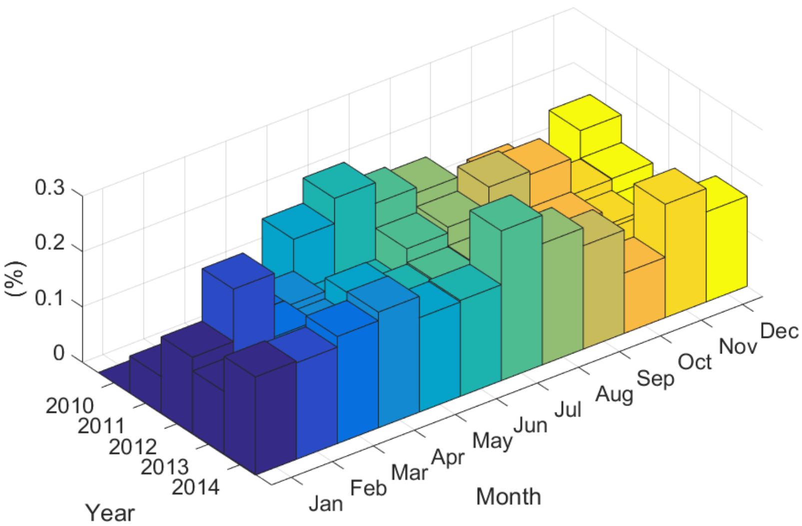
Figure 2.6: Seasonally adjusted liquidity measures



(b) Effective half-spread medians



(c) Realised half-spread medians



(d) Price impact medians

Figure 2.6: Seasonally adjusted liquidity measures (Cont.)

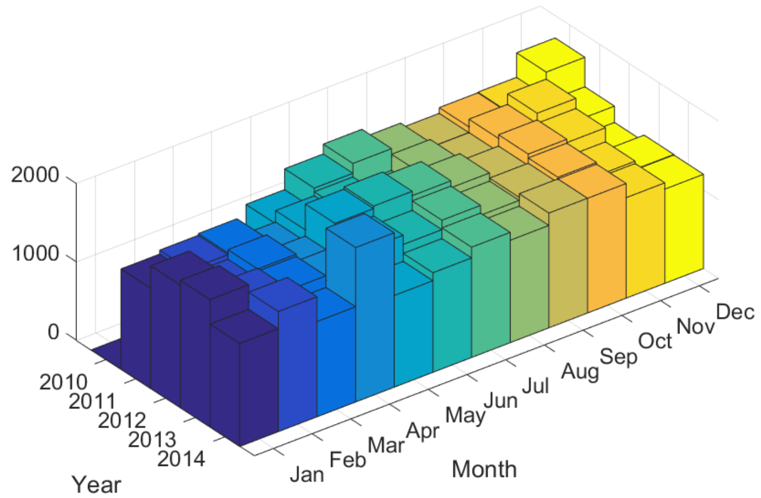
Parameter estimates of the adjustment regressions of the daily trading volume and number of transactions are presented in Table 2.7. Robust standard errors are based on Newey-West estimator. Monthly effects are significant, mostly during the summer and in December. All in all, trading activity is lower and more volatile in the summer and on Mondays. Finally, a significant and negative trend is found in the trading volume and number of transactions series, thus suggesting a decrease in the one-month-ahead NBP forward market trading activity throughout the period analysed.

Table 2.7: Parameter estimates of the adjustment regressions of the daily trading activity variables

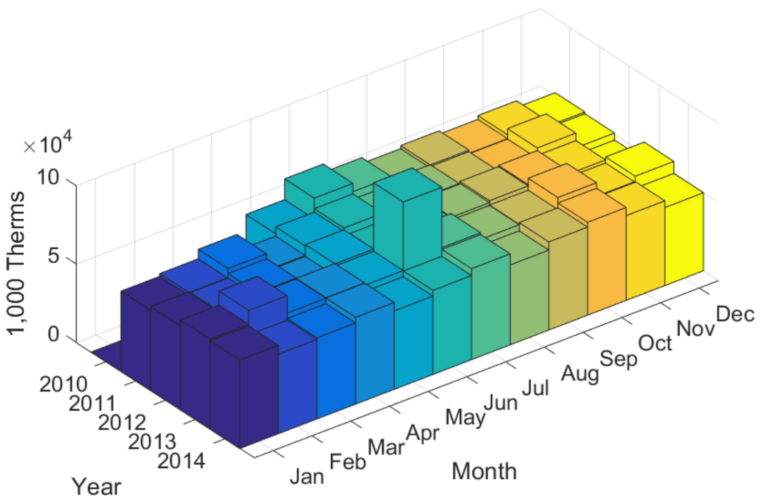
		Trading volume			Number of transactions		
		Coeff.	Std.Err.	t-Stat	Coeff.	Std.Err.	t-Stat
Intercept		8.043***	0.612	13.15	4.653***	0.517	9.006
Month	Feb	0.078	0.066	1.167	0.131**	0.052	2.496
	Mar	-0.145**	0.066	-2.183	-0.166***	0.056	-2.950
	Apr	-0.259***	0.072	-3.596	-0.223***	0.057	-3.864
	May	-0.414***	0.068	-6.031	-0.392***	0.053	-7.405
	Jun	-0.511***	0.076	-6.669	-0.565***	0.063	-8.966
	Jul	-0.610***	0.071	-8.497	-0.580***	0.058	-9.850
	Aug	-0.482***	0.072	-6.668	-0.563***	0.060	-9.374
	Sep	-0.297***	0.072	-4.080	-0.364***	0.059	-6.166
	Oct	-0.179***	0.068	-2.602	-0.227***	0.054	-4.138
	Nov	-0.077	0.071	-1.076	-0.167***	0.060	-2.785
	Dec	-0.729***	0.083	-8.787	-0.845***	0.073	-11.51
Day	Tue	0.243***	0.045	5.318	0.160***	0.037	4.322
	Wed	0.182***	0.048	3.782	0.097**	0.044	2.201
	Thu	0.208***	0.046	4.479	0.124***	0.039	3.169
	Fri	0.077	0.048	1.601	0.021	0.040	0.537
Trend		-0.0002***	0.00001	-16.34	-0.0005***	0.00004	-13.16

Note:***, **, * denote 1%, 5% and 10% significance level, respectively.

The seasonally adjusted series of the trading volume and number of transactions are shown in Figure 2.7. Data are displayed by year and by month. The adjusted series show a reduction of the trading activity in the period 2013-2014, which can be linked with the increase in the measures that was observed above, thus indicating higher transaction costs and lower liquidity in the market.



(a) Number of transactions



(b) Trading volume

Figure 2.7: Seasonally adjusted trading activity variables

Table 2.8 presents the Spearman rank correlation coefficients between the seasonally adjusted daily liquidity measures and trading variables. Correlation is high and positive between effective and realised half-spreads (0.642) and between effective half-spread and price impact (0.541). However, correlation is lower and negative between realised half-spread and price impact (-0.160). Furthermore, correlation is positive between realised half-spread, and number of transactions and trading volume (0.145 and 0.163, respectively), but is negative between price impact, and number of transactions and trading volume (-0.101 and -0.120).

Table 2.8: Correlations between liquidity and trading activity

	Effective half-spread	Realised half-spread	Price Impact	No. of transactions
Realised half-spread	0.642			
Price Impact	0.541	-0.160		
No. of transactions	0.009**	0.145	-0.101	
Trading Volume	0.011*	0.163	-0.120	0.796

Note:***, ** and * denote significance at 1%, 5% and 10%, respectively.

Overall, there is evidence of movements in the one-month-ahead NBP forward market liquidity over the period. In particular, the evolution of the liquidity measures indicate seasonal and decreasing transaction costs in the period analysed. Furthermore, the bivariate correlations confirm the existence of distinct dimensions of liquidity, which were suggested by differences in the distribution of the liquidity measures (Table 2.6).

Parameter estimates of the adjustment regressions accounting for seasonalities and trends in the price returns and order flow series are presented in Table 2.9. Monthly, daily and intraday seasonalities are found in the price return series; only intraday seasonality is found instead in the order flow. Price returns and order flow tend to be higher in the morning, suggesting a positive correlation between their intraday series. Finally, trends are not significant in either series.

The seasonally adjusted price returns and order flow series are used to estimate the price impact measure λ_n in Eq. (2.4). This measure links transaction price returns to order flow and assesses the pressure exerted by trading activity on the one-month-ahead NBP forward market liquidity. The price impact measure λ_n was estimated over 60-minute intervals and fixed rolling window size m=4,500. This rolling window spans two years and corresponds to the 35% of the sample size after resampling T=12,870.

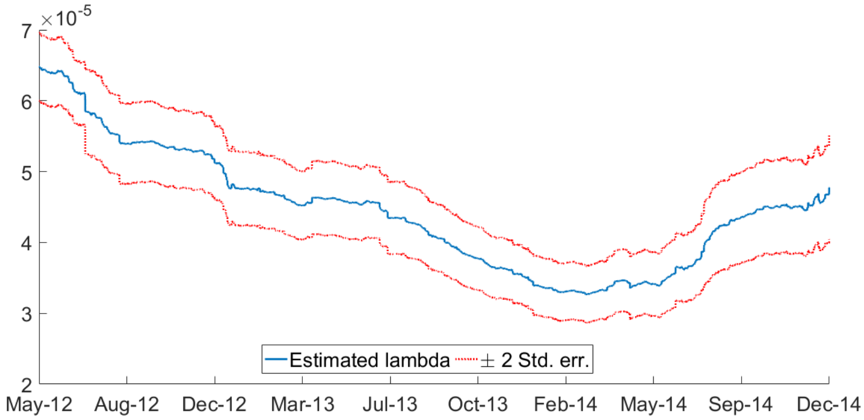
Parameter estimates (blue line) and confidence intervals (red dots) based on Newey-West robust standard errors are depicted in Figure 2.8 (a). A gradual decrease in the measure over the period up to March 2014 and an increase in its level and variance in the subsequent period are observed. When compared with the total order flow over the rolling windows, in Figure 2.8 (b), the time-varying price impact measure λ_n indicates an overall positive correlation between price returns and order flow over the sample, though increasing returns are observed in 2014, when order flow becomes negative and buying pressure reduces.

Table 2.9: Parameter estimates of the adjustment regressions of the price returns and order flow

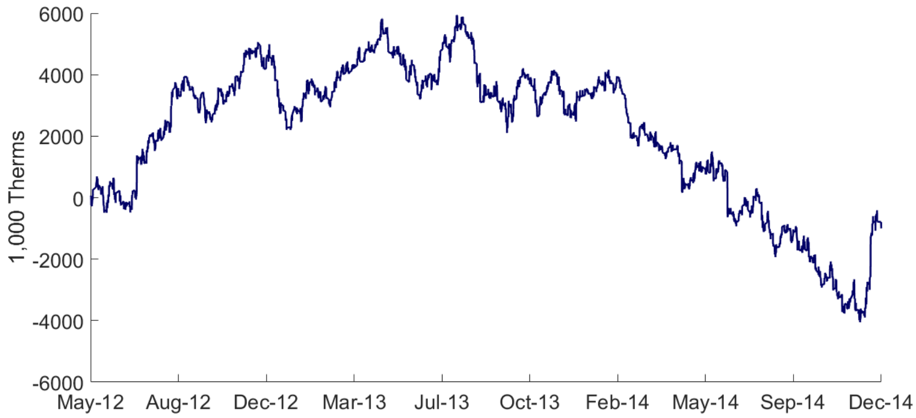
		Price returns			Order flow		
		Coeff.	Std.Er.	t-Stat	Coeff.	Std.Er.	t-Stat
Intercept		-0.0005	0.0003	-1.610	-8.034***	2.619	-3.068
Month	Feb	0.0004	0.0003	1.311	3.925	2.509	1.564
	Mar	0.0005*	0.0003	1.718	3.782*	2.239	1.689
	Apr	-0.0002	0.0003	-0.458	-2.964	2.621	-1.131
	May	0.0000	0.0003	0.068	1.527	2.367	0.645
	Jun	0.0005*	0.0003	1.644	0.668	2.304	0.290
	Jul	0.0002	0.0003	0.853	2.354	2.148	1.096
	Aug	0.0006**	0.0003	2.079	2.615	2.284	1.145
	Sep	0.0007**	0.0003	1.973	2.447	2.370	1.032
	Oct	0.0006**	0.0003	2.000	-0.208	2.372	-0.088
	Nov	0.0006**	0.0003	2.345	1.386	2.179	0.636
	Dec	0.0003	0.0003	1.237	0.797	1.935	0.412
Day	Tue	-0.0005**	0.0002	-2.142	-0.820	1.402	-0.584
	Wed	-0.0002	0.0002	-1.011	1.280	1.385	0.925
	Thu	-0.0001	0.0002	-0.696	0.659	1.356	0.486
	Fri	0.0000	0.0002	-0.050	1.832	1.323	1.385
Hour	8.00	0.0000	0.0003	-0.026	10.35***	2.396	4.320
	9.00	0.00095**	0.0003	3.351	8.075***	2.225	3.629
	10.00	0.00056**	0.0003	2.185	8.652***	2.034	4.253
	11.00	0.00059***	0.0002	2.897	5.728***	1.941	2.952
	12.00	0.00038*	0.0002	1.819	5.861***	1.866	3.140
	13.00	0.00066***	0.0002	3.555	8.079***	1.840	4.391
	14.00	0.00049***	0.0002	2.494	6.171***	1.995	3.094
	15.00	0.0003	0.0002	1.217	2.760	2.148	1.285
Trend		-0.00001	0.00001	-0.96886	-0.00002	0.00013	-0.18110

Note: ***, **, * denote 1%, 5% and 10% significance level, respectively.

On the whole, the results provide a picture of the one-month-ahead NBP forward market liquidity in the period analysed, which confirm the usefulness of assessing different dimensions of liquidity, and the link existing between price return and trading activity. In section 2.7, these results and their implications for researchers, market analysts and policy-makers are discussed. The results from the estimate of the correlations between trading activity, return volatility and liquidity in the one-month-ahead NBP forward market are presented below.



(a) Time-varying measure of price impact λ



(b) Total order flow over the rolling windows

Figure 2.8: Time-varying price impact measure λ and order flow

2.6.2 Co-movements between trading activity, volatility and liquidity in the one-month-ahead NBP forward market

Descriptive statistics of order flow, volatility and spread, resampled at 60-minute frequency, are reported in Table 2.10. The first four moments of the distributions are shown in columns two to five (Mean, Std.Dev., Skewness and Kurtosis, respectively); Median, first (Q_{25}) and third (Q_{75}) interquartile are shown in columns six to eight. With the exception of the measure of spread, the variables exhibit strong asymmetric distributions.

Leptokurtosis is observed in all three series.

Table 2.10: Descriptive statistics of order flow, return volatility and spread

	Mean	Std. Dev.	Skewness	Kurtosis	Median	Q_{25}	Q_{75}
Order flow	6.855	7.927	2.401	15.829	4.000	1.000	10.00
Volatility	0.311	0.548	2.361	265.859	0.170	0.000	0.398
Spread	0.003	0.004	0.000	9.507	0.002	0.001	0.004

Table 2.11 presents the parameter estimates of the adjustment regressions of the variables. Robust standard errors are based on the Newey-West estimator. Seasonal behaviours are observed in the measures of market quality. Order flow is lower during the summer, reflecting weather-dependencies of the natural gas demand. By contrast, price volatility and spread are higher in the summer than in the winter. On a weekly basis, order flow appears to be higher on Tuesdays and Wednesdays, whilst both volatility and spread decrease within the week. Overall, when monthly and daily dynamics are accounted for, there is evidence of a negative correlation between order flow and both volatility and spread, and of a positive correlation between volatility and spread. Conversely, when intra-day patterns are assessed, it appears that positive correlations exist between the three measures, such that both volatility and spread decrease as order flow reduces. Furthermore, a significant negative trend is observed in all measures, thus confirming the previous observations concerning improvements in liquidity (i.e. lower transaction costs) and market stability during the period.

The deseasonalised and detrended measures of order flow, volatility and spread are depicted in Figure 2.9. It appears that when predictable variations are accounted for, return volatility and spread increase in the sample, mostly in 2014, when spread also seems to be more volatile. These findings are supported by the descriptive statistics of the seasonally adjusted measures in Table 2.12, where kurtosis (in column five) is higher when compared to the statistics of the raw series (Table 2.10). All in all, results suggest the importance of allowing for seasonal and trend components when assessing the correlations between trading activity, volatility and liquidity in the one-month-ahead NBP forward market.

Table 2.11: Parameter estimates of the adjustment regressions of order flow, return volatility and spread

		Order flow			Volatility			Spread		
		Coeff	Std.Er.	t-Stat	Coeff	Std.Er.	t-Stat	Coeff	Std.Er.	t-Stat
Intercept		12.31***	0.561	21.92	0.427***	0.023	18.61	0.0046***	0.0003	13.91
Month	Feb	0.635	0.657	0.966	0.051***	0.021	2.385	0.0004	0.0003	1.337
	Mar	-1.454***	0.614	-2.368	0.039*	0.021	1.853	0.0004	0.0003	1.229
	Apr	-0.660	0.605	-1.090	0.057**	0.026	2.225	0.0013***	0.0003	4.423
	May	-1.708***	0.550	-3.103	0.046**	0.021	2.153	0.0020***	0.0004	4.846
	Jun	-2.526***	0.570	-4.433	0.050**	0.023	1.914	0.0019***	0.0004	4.391
	Jul	-2.579***	0.540	-4.776	0.045*	0.025	1.801	0.0017***	0.0004	4.073
	Aug	-2.342***	0.560	-4.181	0.052***	0.022	2.423	0.0018***	0.0003	5.420
	Sep	-1.367***	0.564	-2.425	0.081***	0.033	2.450	0.0012***	0.0003	3.704
	Oct	-0.542	0.585	-0.926	0.020	0.025	0.798	0.0009***	0.0003	2.989
	Nov	-1.096*	0.598	-1.832	-0.012	0.018	-0.667	0.0003	0.0004	0.819
	Dec	-4.616***	0.498	-9.268	-0.016	0.020	-0.823	0.0004	0.0003	1.196
Day	Tue	1.121***	0.274	4.095	-0.045**	0.020	-2.270	-0.0006***	0.0002	-3.875
	Wed	0.783***	0.314	2.497	-0.066***	0.020	-3.262	-0.0008***	0.0002	-4.498
	Thu	0.182	0.302	0.604	-0.089***	0.019	-4.683	-0.0008***	0.0002	-5.142
	Fri	0.049	0.285	0.172	-0.070***	0.020	-3.426	-0.0007***	0.0002	-4.379
Hour	8.00	-0.667**	0.335	-1.994	0.296***	0.024	12.33	0.0029***	0.0002	15.562
	9.00	-0.054	0.367	-0.146	0.067***	0.023	2.878	0.0001	0.0001	1.067
	10.00	-2.665***	0.313	-8.512	-0.0001	0.024	-0.006	-0.0003***	0.0001	-2.370
	11.00	-3.833***	0.317	-12.089	-0.084***	0.015	-5.772	-0.0006***	0.0001	-5.149
	12.00	-5.593***	0.296	-18.907	-0.128***	0.016	-8.272	-0.0007***	0.0001	-6.281
	13.00	-5.382***	0.271	-19.829	-0.101***	0.013	-7.726	-0.0006***	0.0001	-5.644
	14.00	-3.736***	0.296	-12.614	-0.054***	0.013	-4.095	-0.0004***	0.0001	-3.404
	15.00	-1.730***	0.323	-5.360	-0.012	0.016	-0.760	-0.0002***	0.0001	-2.339
Trend		-0.0003***	0.00003	-9.08166	-0.00002***	0.000002	-8.005	-0.00004***	0.000003	-11.100

Note: ***, **, * denote 1%, 5% and 10% significance level, respectively.

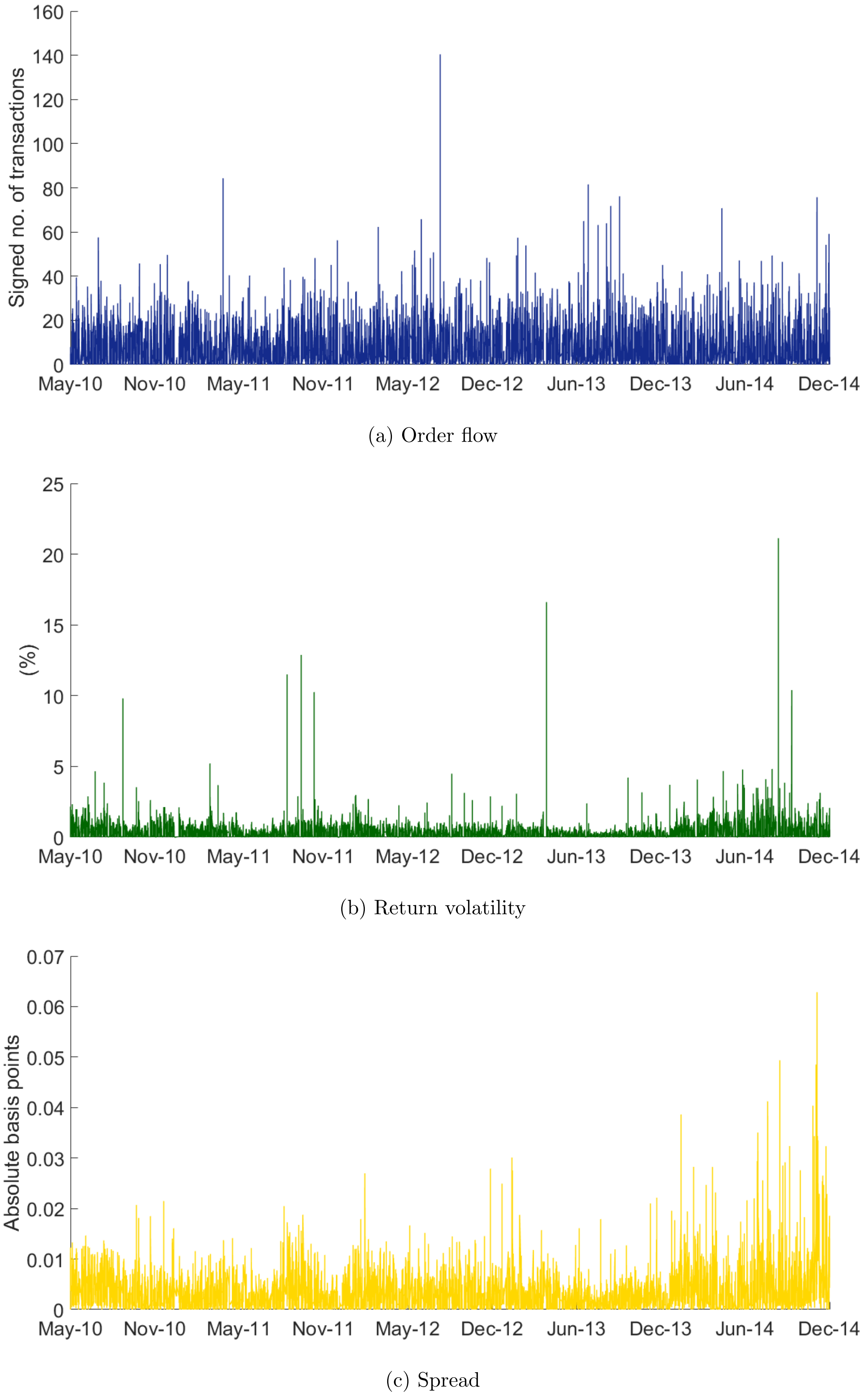


Figure 2.9: Deseasonalised and detrended measures of order flow, volatility and spread

Table 2.12: Descriptive statistics of deseasonalised and detrended order flow, volatility and spread measures

	Mean	Std. Dev.	Skewness	Kurtosis	Median	Q_{25}	Q_{75}
Order flow	6.855	7.927	2.574	18.900	4.722	1.400	9.911
Volatility	0.311	0.548	3.811	353.133	0.180	0.029	0.432
Spread	0.003	0.004	0.000	30.824	0.002	0.001	0.004

Parameter estimates of the VAR model for the adjusted order flow, volatility and spread are reported in Table 2.13. A 9-order-lag VAR was identified according to SIC. Residual diagnostics indicate serial independence at the 2^{nd} order of lags and 1% significance level. Heteroscedasticity is observed at the same order of lags and level of significance. Diagnostic tests have been also performed on the VAR at lower order of lags to examine possible overfitting. Serial correlation and ARCH tests support the specification that was based on the information criterion. The VAR equations are estimated by ordinary least squares and inference is based on Newey-West robust standard errors.

Strong positive correlations are noticed between the variables. There is evidence of a positive correlation between order flow and volatility, and between volatility and spread. Higher volatility appears to be followed by greater spread, whilst larger spread is associated with subsequent higher volatility. Finally, the effect of spread on the subsequent order flow is mixed. The observed correlations between pairs of variables are apparent not only through the t-statistics of the individual estimated coefficients, but also by χ^2-statistics (rows thirty-two to thirty-four of Table 2.13), where the null hypothesis that on all coefficients of order flow, volatility and spread are simultaneously zero is tested. The adjusted R^2 coefficient (row thirty-one of the table) of the order flow and volatility equations is approximately 0.07, whilst the spread equation coefficient is approximately 0.34. Altogether, the correlation between spread and volatility is stronger, which is in line with evidence from financial markets (Chordia et al., 2005b; Danielsson and Payne, 2012). In order to assess co-movements between order flow, volatility and spread, and liquidity drivers in the one-month-ahead NBP forward market, the VMA representation in Eq. (2.6) is estimated and the impulse response functions are computed.

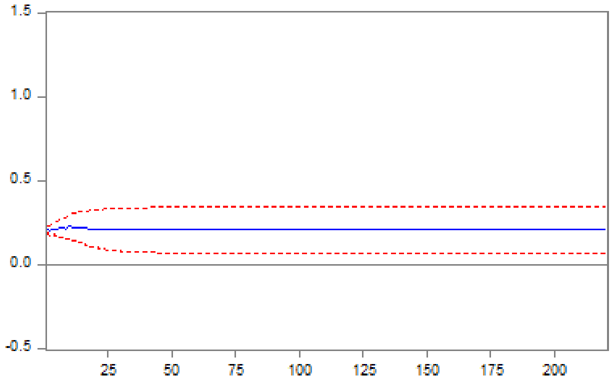
Figure 2.10 shows the cumulative impulse responses across two-hundred-twenty 60-minute intervals, corresponding to one month (blue line), along with 95% confidence intervals (red dots). The VMA standard errors are calculated by Monte Carlo simulation, using 10,000 replications.

Table 2.13: Parameter estimates of the VAR model of order flow, volatility and spread

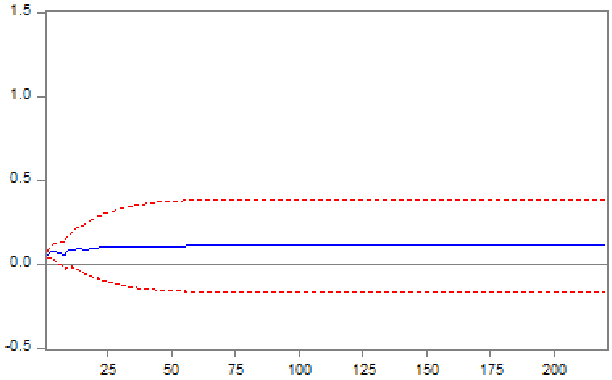
	Order flow (V)			Volatility ($\|R\|$)			Spread (S)		
	Coeff	Std.Er.	t-Stat	Coeff	Std.Er.	t-Stat	Coeff	Std.Er.	t-Stat
Intercept	0.4524***	0.027	16.62	0.2338***	0.038	6.15	0.1424***	0.051	2.80
V_t	-	-	-	0.2121***	0.012	17.60	0.0123	0.012	1.03
V_{t-1}	0.1603***	0.013	3.40	-0.0516***	0.008	-6.14	-0.0132	0.012	-1.10
V_{t-2}	0.0486***	0.015	2.70	-0.0044	0.007	-0.60	0.0035	0.009	0.37
V_{t-3}	0.0520***	0.011	0.03	-0.0198***	0.007	-2.69	0.0078	0.013	0.59
V_{t-4}	-0.0093	0.010	2.23	-0.0056	0.008	-0.72	-0.0169**	0.009	-1.93
V_{t-5}	0.0209**	0.008	0.13	-0.0113	0.007	-1.54	-0.0035	0.008	-0.43
V_{t-6}	0.0085	0.010	2.17	-0.0049	0.007	-0.68	-0.0066	0.008	-0.79
V_{t-7}	0.0399***	0.008	-0.09	-0.0237***	0.007	-3.38	0.0009	0.009	0.09
V_{t-8}	0.0539***	0.009	-1.11	-0.0092	0.007	-1.29	0.0214**	0.009	2.46
V_{t-9}	0.0725***	0.010	0.27	-0.0131	0.008	-1.55	-0.0058	0.010	-0.60
$\|R_t\|$	-	-	-	-	-	-	0.2050***	0.039	5.28
$\|R_{t-1}\|$	0.0455***	0.010	4.52	0.0331***	0.011	3.12	-0.0162	0.013	-1.26
$\|R_{t-2}\|$	0.0411***	0.010	4.08	0.0433***	0.013	3.23	-0.0114	0.012	-0.93
$\|R_{t-3}\|$	0.0003	0.010	0.03	0.0257***	0.010	2.48	-0.0226**	0.011	-2.04
$\|R_{t-4}\|$	0.0223**	0.010	2.21	0.0351***	0.012	3.01	-0.0044	0.009	-0.51
$\|R_{t-5}\|$	0.0010	0.010	0.10	0.0638***	0.012	5.12	0.0003	0.011	0.03
$\|R_{t-6}\|$	0.0221**	0.010	2.19	0.0513***	0.013	3.82	0.0072	0.010	0.71
$\|R_{t-7}\|$	-0.0007	0.010	-0.07	0.0317***	0.010	3.23	-0.0099	0.010	-0.97
$\|R_{t-8}\|$	-0.0097	0.010	-0.96	0.0321***	0.011	2.99	-0.0051	0.009	-0.59
$\|R_{t-9}\|$	0.0027	0.010	0.27	0.0357***	0.010	3.70	-0.0052	0.009	-0.56
S_t	-	-	-	-	-	-	-	-	-
S_{t-1}	0.0022	0.013	0.17	0.0088	0.011	0.78	0.4032***	0.029	13.7
S_{t-2}	-0.0005	0.015	-0.04	0.0177	0.012	1.52	0.0449**	0.019	2.42
S_{t-3}	-0.0169	0.013	-1.29	0.0025	0.011	0.23	0.0495***	0.011	4.37
S_{t-4}	-0.0056	0.013	-0.44	0.0238**	0.012	2.03	0.0211*	0.012	1.70
S_{t-5}	-0.0467***	0.011	-4.08	0.0001	0.011	0.01	0.0550***	0.016	3.49
S_{t-6}	0.0007	0.012	0.05	-0.0058	0.012	-0.49	0.0196	0.014	1.39
S_{t-7}	-0.0020	0.010	-0.19	0.0059	0.013	0.47	0.0452***	0.015	3.08
S_{t-8}	-0.0066	0.011	-0.58	0.0106	0.010	1.030	0.0084	0.014	0.60
S_{t-9}	0.0228**	0.012	1.92	0.0237**	0.011	2.089	0.0936***	0.017	5.40
Adjusted R^2			0.070			0.073			0.344
χ^2 Order flow			395.9***			322.4***			14.48
χ^2 Volatility			43.25***			65.94***			34.41***
χ^2 Spread			38.78***			18.29**			304.1***

Note: ***, ** and * denote significance at 1%, 5% and 10%, respectively.

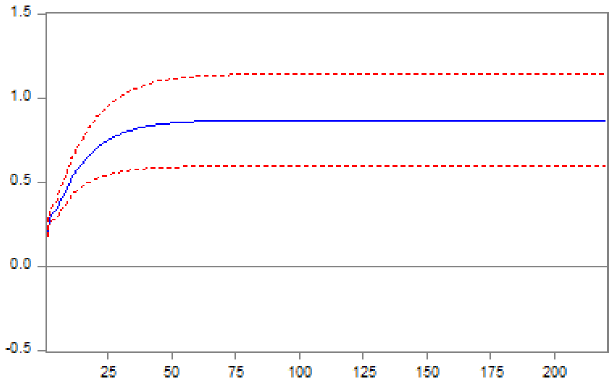
The cumulative response of volatility and spread to one-standard-deviation shock in order flow are depicted in Figure 2.10 (a)-(b), whilst the cumulative response of spread to one-standard-deviation shock in volatility is shown in Figure 2.10 (c). Altogether, the plots indicate greater response of spread to volatility shocks across time. Yet, although it appears that the spread's cumulative response to order flow is insignificant, results in Figure 2.10 imply that shocks to order flow transmit to spread through volatility over time. Therefore, both volatility and spread are positively correlated to order flow, with spread strongly positively correlated with volatility. These findings are robust to re-orderings of the three variables in the VAR specification. Hence, the higher the order flow, the higher the volatility and, in turn, the spread, the lower is liquidity in the one-month-ahead NBP forward market.



(a) Volatility to order flow



(b) Spread to order flow

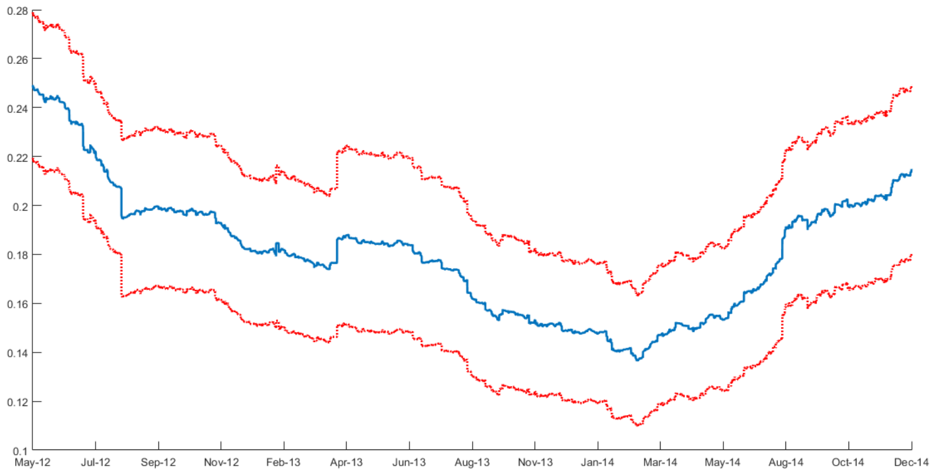


(c) Spread to volatility

Figure 2.10: Cumulative impulse response functions

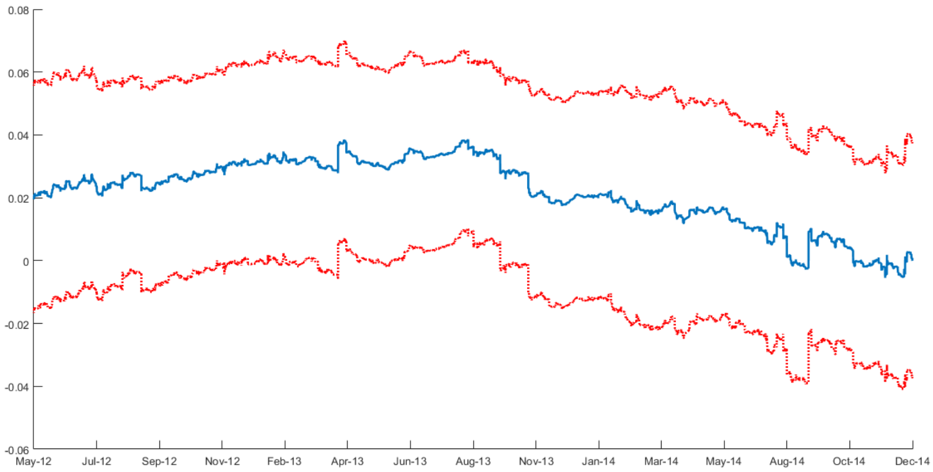
Rolling estimates of the coefficients $\alpha_{|R|,0}$, $\alpha_{S,0}$, and $\beta_{S,0}$ in Eq. (2.5), representing the contemporaneous correlations between order flow, volatility and spread are shown in Figure 2.11 (blue line), along with their 95% confidence intervals (red dots). The positive correlation between order flow and volatility (Figure 2.11 (a)) appears to reduce during the period May 2010-March 2013, when volatility is low (Figure 2.9 (b)). By contrast, this correlation increases from the second quarter 2014 onwards, when volatility also increases. Figure 2.11 (b) suggests a reduction of the correlation between order flow and spread during the period August 2013-December 2014, relative to the previous period in the sample. Finally, the correlation between volatility and spread is positive across the sample, though its variability grows from 2012 onwards (Figure 2.11 (c)).

On the whole, the results give a picture of what may drive liquidity in the one-month-ahead NBP forward market and confirm the time-varying features of the links existing between trading activity, volatility and liquidity in the period analysed. In Section 2.7, these results and their implications for researchers, market analysts and policy-makers are discussed. In the next subsection, results on the possible impacts of REMIT on liquidity in the one-month-ahead NBP forward market are presented.

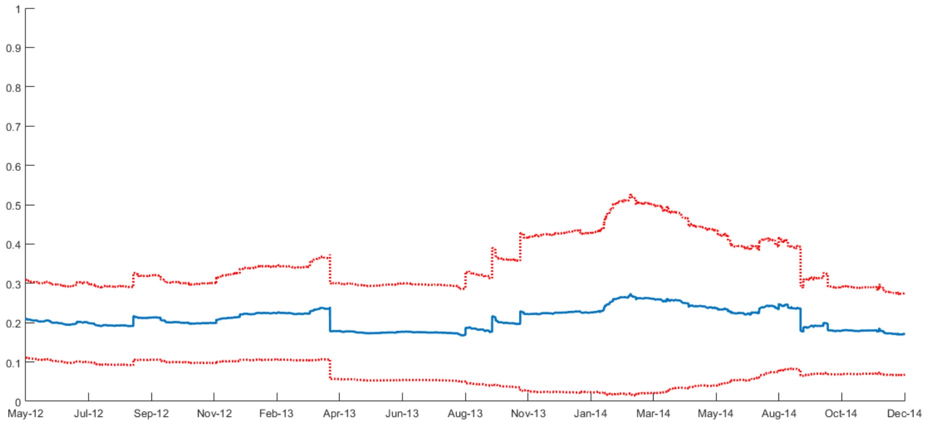


(a) Correlation between order flow and volatility

Figure 2.11: Time-varying contemporaneous correlations between measures of order flow, volatility and spread



(b) Correlation between order flow and spread



(c) Correlation between volatility and spread

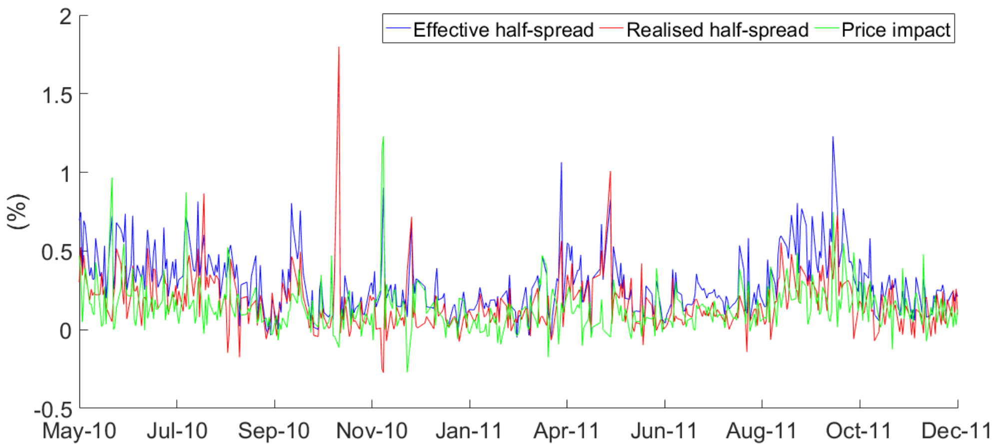
Figure 2.11: Time-varying contemporaneous correlations between measures of order flow, volatility and spread (Cont.)

2.6.3 The impact of REMIT

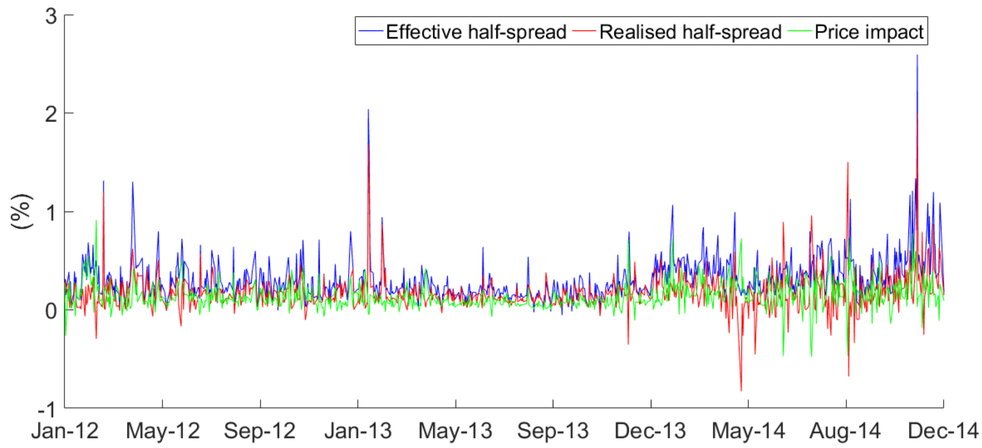
The adjusted daily effective half-spread, realised half-spread and price impact, observed in the Pre-REMIT and Post-REMIT periods, are depicted in Figure 2.12. The Pre-REMIT period runs from 7 May, 2010 to 27 December, 2011 thus spanning 412 trading days before the entering into force of REMIT. The Post-REMIT period covers 754 trading days, from 2 January 2012 to 29 December 2014. Therefore, the Pre- and Post-REMIT adjusted measures are computed over the intervals $t \in [-413, -1]$ and $t \in [+1, 754]$, respectively.

A decrease in the liquidity measures can be noticed following the entering into force of

REMIT (2012-13). However, their level and volatility increase during 2014, in particular in the last quarter of the year.



(a) Pre-REMIT



(b) Post-REMIT

Figure 2.12: Seasonally adjusted liquidity measures in the pre- and post-REMIT periods

Descriptive statistics of the seasonally adjusted daily liquidity measures and trading activity measures, which are observed in the Pre- and Post-REMIT periods, are presented in Table 2.14. T-tests and non-parametric sign tests of the means and medians fail to reject the null hypothesis of equality in the pre- and post-event sub-samples. One-tail F-tests reject the null hypothesis of equal variances across the two sub-samples for all variables, thus confirming the pattern observed above. Parameter estimates from the adjustment regressions of the price returns and order flow are reported in Table 2.15 and indicate a decrease in the price impact measure λ_n. The Chow's test rejects the null hypothesis of an identical pattern across sub-samples, and indicates a reduction in the pressure exerted by trading activity on prices.

Table 2.14: Descriptive statistics of the seasonally adjusted daily liquidity measures and trading activity variables in the pre- and post-REMIT

	Mean	St. Dev.	Q_{25}	Median	Q_{75}	ρ_1
Pre-REMIT						
Effective half-spread	0.302	0.209	0.157	0.258	0.396	0.434
Realised half-spread	0.169	0.173	0.062	0.142	0.250	0.275
Price impact	0.140	0.160	0.045	0.111	0.194	0.268
Number of transactions	65.47	22.39	56.66	58.51	63.84	0.145
Trading volume	2638	466	2498	2514	2576	0.0192
Post-REMIT						
Effective half-spread	0.317	0.230**	0.177	0.260	0.395	0.412
Realised half-spread	0.173	0.193**	0.083	0.144	0.236	0.139
Price impact	0.140	0.135**	0.065	0.108	0.202	0.184
Number of transactions	67.58	35.40**	56.77	58.84	65.29	0.040
Trading volume	2699	1811**	2499	2516	2572	0.0129

Note: ***, **, * denote 1%, 5% and 10% significance level, respectively.

Table 2.15: Parameter estimates from the adjustment regressions of the price returns and order flow in the Pre- and Post-REMIT

Event	Constant	Lambda	$Adj-R^2$
Pre-REMIT	0.469** (0.235)	0.090***(0.01)	0.291
Post-REMIT	-0.228 (0.183)	0.076***(0.006)	0.228

Note: ***, **, * denote 1%, 5% and 10% significance level, respectively.

Parameter estimates of the VAR model in the Pre-REMIT and Post-REMIT periods are presented in Tables 2.16 and 2.17, respectively. Autocorrelation is stronger in the Post-REMIT period compared to the Pre-REMIT. In both sub-samples, contemporaneous correlations are significant and in line with results from the full sample (Table 2.13). Nonetheless, in the post-REMIT period lower and less persistent correlation is observed between spread and subsequent volatility, compared to both the Pre-REMIT period and the full sample. These observations are inferred through t-statistics of the estimated coefficients, likewise from the χ^2-statistics in the final row of Tables 2.16 and 2.17. Overall, the adjusted R^2 coefficients from the VAR specifications in the subsamples are comparable to the corresponding values that were observed in the full sample (Table 2.13).

Chow's tests on the single equations significant differences in the estimated equations

Table 2.16: Parameter estimates of the VAR: Pre-REMIT

	Order flow (V)			Volatility ($\|R\|$)			Spread (S)		
	Coeff	Std.Er.	t-Stat	Coeff	Std.Er.	t-Stat	Coeff	Std.Er.	t-Stat
Intercept	0.4082***	0.043	9.54	0.2143***	0.056	3.82	0.2109***	0.029	7.40
V_t	-	-	-	0.2564***	0.016	15.6	0.0269	0.019	1.39
V_{t-1}	0.1836***	0.020	9.09	-0.0591***	0.015	-3.95	-0.0275*	0.015	-1.80
V_{t-2}	0.0293	0.019	1.58	0.0013	0.015	0.09	0.0100	0.013	0.75
V_{t-3}	0.0385**	0.019	2.05	-0.029**	0.012	-2.39	-0.0161	0.013	-1.20
V_{t-4}	-0.0273	0.020	-1.39	0.0036	0.014	0.26	-0.0197	0.013	-1.52
V_{t-5}	0.0354**	0.018	1.98	0.0196	0.014	1.36	-0.0002	0.013	-0.02
V_{t-6}	-0.0141	0.017	-0.84	-0.0057	0.014	-0.42	-0.0133	0.013	-0.99
V_{t-7}	0.0463**	0.019	2.40	-0.0142	0.014	-0.99	-0.0245*	0.013	-1.89
V_{t-8}	0.0602***	0.019	3.19	0.0140	0.014	1.03	0.0286**	0.013	2.21
V_{t-9}	0.0615***	0.018	3.34	-0.0214	0.014	-1.59	-0.0051	0.013	-0.39
$\|R_t\|$	-	-	-	-	-	-	0.2093***	0.054	3.89
$\|R_{t-1}\|$	0.0509***	0.013	3.80	0.0272	0.023	1.18	0.0017	0.023	0.07
$\|R_{t-2}\|$	0.0427***	0.018	2.36	0.0235	0.023	1.01	-0.0295**	0.014	-2.11
$\|R_{t-3}\|$	0.0133	0.015	0.88	0.0157	0.017	0.95	-0.0156	0.011	-1.39
$\|R_{t-4}\|$	0.0334**	0.016	2.13	0.0224	0.015	1.53	0.0019	0.012	0.15
$\|R_{t-5}\|$	0.0153	0.014	1.11	0.0273*	0.014	1.92	-0.0006	0.014	-0.04
$\|R_{t-6}\|$	0.0579***	0.022	2.59	0.0314*	0.013	2.50	0.0176	0.021	0.85
$\|R_{t-7}\|$	0.0064	0.011	0.58	0.0174	0.013	1.34	0.0014	0.021	0.07
$\|R_{t-8}\|$	0.0210	0.018	1.17	0.0220	0.016	1.39	0.0016	0.014	0.11
$\|R_{t-9}\|$	0.0436**	0.017	2.57	0.0020	0.013	0.16	-0.0017	0.011	-0.15
S_t	-	-	-	-	-	-	-	-	-
S_{t-1}	-0.0020	0.023	-0.09	0.0047	0.024	0.19	0.2962***	0.032	9.33
S_{t-2}	-0.0294	0.023	-1.27	0.0633***	0.024	2.68	0.0921***	0.025	3.68
S_{t-3}	-0.0302	0.024	-1.27	0.0069	0.021	0.33	0.0410**	0.021	1.95
S_{t-4}	0.0138	0.025	0.54	0.0281	0.020	1.44	0.0470***	0.018	2.63
S_{t-5}	-0.0435*	0.022	-1.95	-0.0216	0.021	-1.03	0.0437**	0.024	1.84
S_{t-6}	0.0022	0.023	0.09	0.0684***	0.024	2.81	0.0239	0.023	1.02
S_{t-7}	-0.0183	0.021	-0.86	-0.0201	0.021	-0.94	0.0248	0.021	1.19
S_{t-8}	-0.0179	0.022	-0.82	0.0073	0.020	0.36	-0.0100	0.019	-0.53
S_{t-9}	0.0083	0.024	0.35	0.0323*	0.018	1.82	0.0721***	0.018	4.00
Adjusted R^2			0.089			0.072			0.271
χ^2 Order flow			190.4***			287.1***			16.52*
χ^2 Volatility			41.36***			13.31			29.82***
χ^2 Spread			17.43**			20.82**			314.2***

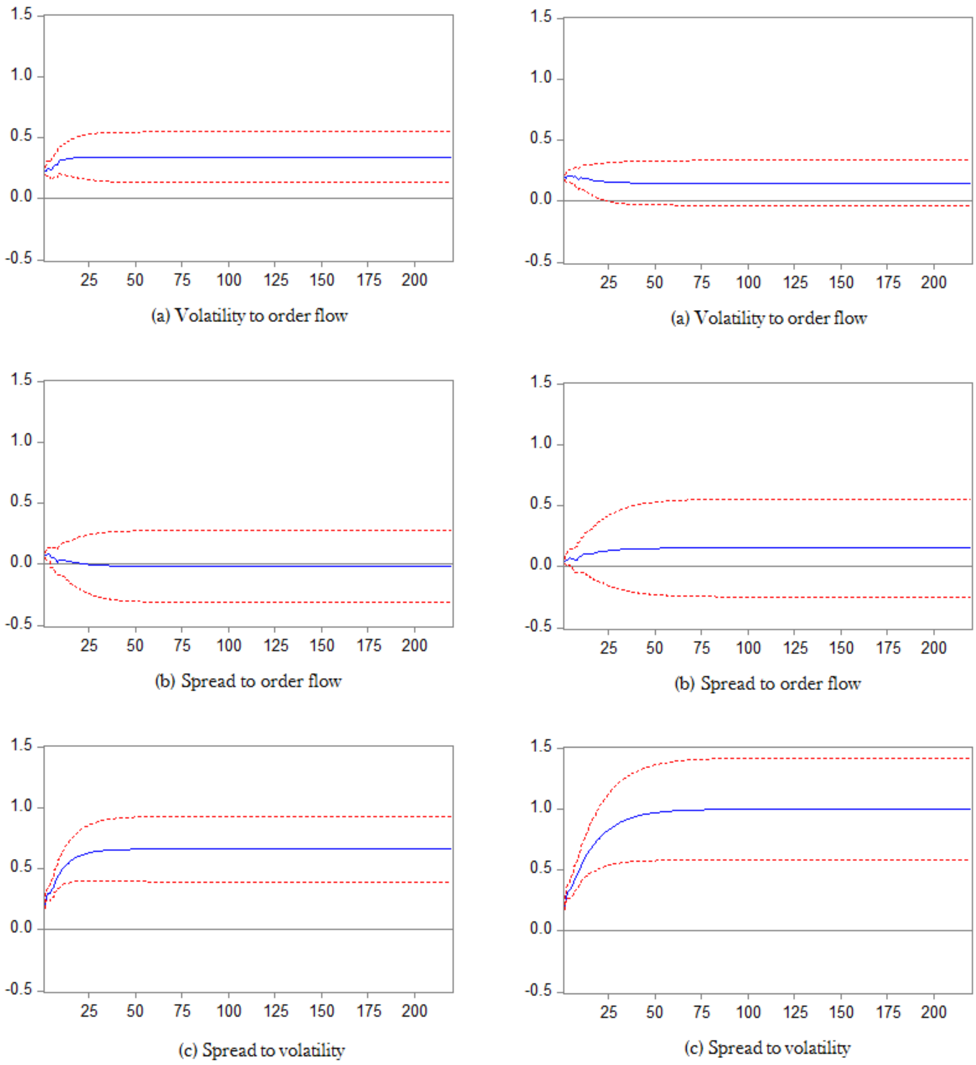
Note: ***, ** and * denote significance at 1%, 5% and 10%, respectively.

across sub-samples, thus denoting changes in the considered relationships following REMIT. These changes can be better assessed by comparing the cumulative impulse response functions estimated in the Pre-REMIT (Figure 2.13 left) and Post-REMIT (Figure 2.13, right) sub-samples. Increased responses of spread both to order flow and volatility are observed in the Post-REMIT period compared to the Pre-REMIT; by contrast, the response of volatility to order flow is found to be lower in the post-REMIT than in the pre-REMIT. Together the results indicate that changes have occurred in the co-movements between trading activity, volatility and liquidity and in the price pressure measure in the one-month-ahead NBP forward market following the entering into force of REMIT, although these changes have not been observed in the different dimensions of liquidity.

Table 2.17: Parameter estimates of the VAR: Post-REMIT

	Order flow (V)			Volatility ($\|R\|$)			Spread (S)		
	Coeff	Std.Er.	t-Stat	Coeff	Std.Er.	t-Stat	Coeff	Std.Er.	t-Stat
Intercept	0.4959***	0.0354	14.02	0.2265***	0.0477	4.75	0.1312**	0.0652	2.01
V_t	-	-	-	0.1953***	0.0148	13.23	0.0050	0.0150	0.34
V_{t-1}	0.1466***	0.0195	7.51	-0.0467***	0.0100	-4.69	-0.0079	0.0159	-0.49
V_{t-2}	0.0542***	0.0137	3.96	-0.0055	0.0084	-0.66	0.0001	0.0121	0.01
V_{t-3}	0.0557***	0.0145	3.85	-0.0135	0.0092	-1.47	0.0175	0.0178	0.98
V_{t-4}	-0.0038	0.0124	-0.30	-0.0064	0.0095	-0.68	-0.0176	0.0112	-1.57
V_{t-5}	0.0140	0.0128	1.10	-0.0223***	0.0083	-2.68	-0.0067	0.0100	-0.67
V_{t-6}	0.0146	0.0131	1.11	-0.0047	0.0087	-0.54	-0.0039	0.0104	-0.37
V_{t-7}	0.0358***	0.0131	2.73	-0.0273***	0.0080	-3.41	0.0113	0.0124	0.91
V_{t-8}	0.0509***	0.0144	3.54	-0.0192**	0.0085	-2.25	0.0169	0.0111	1.53
V_{t-9}	0.0761***	0.0147	5.16	-0.0075	0.0107	-0.71	-0.0056	0.0126	-0.44
$\|R_t\|$	-	-	-	-	-	-	0.2017***	0.0520	3.88
$\|R_{t-1}\|$	0.0461***	0.0197	2.34	0.0340***	0.0108	3.14	-0.0182*	0.0139	-1.31
$\|R_{t-2}\|$	0.0443**	0.0204	2.17	0.0486***	0.0163	2.99	0.00005	0.0163	0.003
$\|R_{t-3}\|$	-0.0026	0.0140	-0.18	0.0271**	0.0133	2.04	-0.0258**	0.0160	-1.61
$\|R_{t-4}\|$	0.0185	0.0129	1.44	0.0379**	0.0165	2.30	-0.0069	0.0114	-0.61
$\|R_{t-5}\|$	-0.0051	0.0091	-0.56	0.0807***	0.0156	5.18	0.0031	0.0158	0.20
$\|R_{t-6}\|$	0.0056	0.0091	0.62	0.0543***	0.0190	2.86	0.0034	0.0112	0.31
$\|R_{t-7}\|$	-0.0014	0.0102	-0.14	0.0361***	0.0138	2.62	-0.0116	0.0112	-1.04
$\|R_{t-8}\|$	-0.0226**	0.0091	-2.48	0.0342**	0.0139	2.46	-0.0055	0.0106	-0.52
$\|R_{t-9}\|$	-0.0161	0.0102	-1.58	0.0492***	0.0138	3.57	-0.0033	0.0128	-0.26
S_t	-	-	-	-	-	-			
S_{t-1}	0.0003	0.0158	0.02	0.0144	0.0129	1.12	0.4364***	0.0347	12.60
S_{t-2}	0.0072	0.0179	0.40	0.0029	0.0133	0.22	0.0230	0.0226	1.02
S_{t-3}	-0.0139	0.0158	-0.88	0.0044	0.0128	0.35	0.0557***	0.0138	4.03
S_{t-4}	-0.0113	0.0148	-0.76	0.0206	0.0141	1.46	0.0097	0.0157	0.62
S_{t-5}	-0.0491***	0.0133	-3.69	0.0118	0.0138	0.86	0.0607***	0.0190	3.19
S_{t-6}	-0.0009	0.0143	-0.06	-0.032**	0.0130	-2.49	0.0136	0.0168	0.81
S_{t-7}	0.0028	0.0119	0.24	0.0195	0.0150	1.30	0.0522***	0.0179	2.92
S_{t-8}	-0.0057	0.0135	-0.42	0.0100	0.0118	0.84	0.0105	0.0170	0.62
S_{t-9}	0.0257*	0.0137	1.87	0.0234*	0.0136	1.72	0.0967***	0.0212	4.57
Adjusted R^2			0.062			0.075			0.365
χ^2 Order flow			228.3***			182.5***			8.741
χ^2 Volatility			27.57***			55.52***			18.16**
χ^2 Spread			32.66***			20.79**			273.7***

Note: ***, ** and * denote significance at 1%, 5% and 10%, respectively.



Pre-REMIT Post-REMIT

Figure 2.13: Cumulative impulse response functions in the Pre- and Post-REMIT periods

On the sensitivity of the results to the start date of REMIT

Results of the intervention analysis indicate a positive trend in the liquidity measures after REMIT, as inferred by statistically significant coefficients β in Eq. (2.7) of the three measures. These results support the pattern that is observed in Figure 2.12 - Chart (b) and may be explained by the observed increase in the measures during 2014.

Parameter estimates of the regression model in Eq. (2.8) indicate a reduction in the price pressure exerted by order flow after REMIT, as inferred through the coefficient δ, which ranges from -0.02 (standard error 0.03), by assuming the day following the entering into force of REMIT as starting day for the intervention period, to -0.021 (standard error 0.03), when a three-month time lag is assumed for REMIT to impact trading activity in the NBP forward market. These results are in line with the previous parameter estimates and Chow's test in Table 2.15.

Results from the trend-intervention analysis indicate a decrease in the correlation between order flow and volatility, as inferred by the coefficient ϕ in Eq. (2.9). Over a three-month interval, this coefficient ranges from -0.05 (standard error 0.01), with the intervention period starting on 29 December 2011, to -0.06 (standard error 0.02), with the intervention period starting on 28 March 2012. These results are in line with the VAR analysis summarised in Tables 2.16-2.17 and the cumulative impulse response function in Figure 2.13. By contrast, when the correlations between spread and order flow and volatility are investigated, the hypothesis of changes in these correlations is rejected at all considered starting dates of the intervention period over the three-month interval, as inferred by insignificant coefficients φ and ψ in Eq. (2.9).

2.7 Discussion

The measures of spread and price impact drawn from the financial literature and used in this chapter were designed to capture different dimensions of liquidity in the one-month-ahead NBP forward market. On the whole, they suggested an improvement in liquidity during the period May 2010 - December 2014, which is in line with what was reported in the same period by Ofgem, the independent regulator for gas and electricity markets in the UK (Ofgem, 2016). A negative trend was observed in the transaction costs, which were on average 0.3%, according to the mean daily percentage effective half-spread, and are in line with what was observed by Marshall et al. (2012) concerning the US natural gas futures market. It is noteworthy that results in this chapter identify long-term dynamics in the one-month-ahead NBP forward market, since the analysis accounted for predictable variations in the time series. The importance of deseasonalising and detrending measures of liquidity and trading activity in the natural gas market might be inferred when the seasonally adjusted measures in Figure 2.6 are compared with the *churn ratio* in Figure 2.1, and the unadjusted measures, in Figure 2.5. As observed and discussed above, low *churn ratio* was observed during the winter, when traded volumes were lower compared to the physical deliveries, and indicates low liquidity. This pattern is unclear when the unadjusted measures are considered, but becomes noticeable when observing the adjusted measures, thus suggesting that liquidity in the one-month-ahead NBP forward market is affected by seasonalities and may be driven by trading activity.

These findings support the market microstructure theory from financial markets (Glosten and Milgrom, 1985; Kyle, 1985; Easley and O'Hara, 1987), according to which trading activity affects liquidity, and are also in line with the *churn ratio* (Figure 2.1). Nonetheless, the *churn ratio* does not allow the identification of different dimensions of liquidity nor to measure their relative contribution. By contrast, the liquidity measures in this chapter indicate that 55% of transaction costs were explained by their non-informational component, as represented by the mean daily percentage realised half-spread. Furthermore, given the higher and positive correlation between the effective half-spread and the realised half-spread in relation to the price impact (Table 2.6), these measures imply that transaction costs in the one-month-ahead NBP forward market would be more strongly linked to inventories than to asymmetric information. This result tallies with the higher and positive correlation between realised half-spread and trading activity (Table 2.8).

As described in the seminal work of Stoll (1978), greater trading activity may induce inventory imbalances in the market, leading to changes in the bid-ask spreads and consequently higher transaction costs, thus reducing liquidity. An additional interpretation of these findings is that trading activity erodes dealers' inventory positions, and thus increases the cost of immediacy. This view is supported by the estimates of price impact λ_n, which on the whole imply a positive correlation between the one-month-ahead NBP forward price returns and the order flow, as previously observed in the context of financial markets (Payne, 2003). In addition, the gradual decrease in this correlation, which was observed in the period 2010-13, implies lower immediacy cost and greater depth and resilience of the market, which were likely driven by lower demand for natural gas, high inventory and reduced trading activity in the period. The correlation between price returns and order flow increased in 2014, when order flow became negative, implying greater inventory imbalances.

The dynamic of the price impact λ_n tallies with the estimates of the correlation between volatility, as proxied by the absolute returns, and trading activity in the VAR model (Figure 2.11 (a)). This correlation was found to be positive and decreasing in the period 2010-13, when price impact was also observed to decrease. The correlation between volatility and trading activity increased in 2014, at the same time with an increase in the measure of price impact λ_n and inventory imbalances. Overall, these dynamics are in line with the theoretical framework described above and the hypothesis that trading activity in the NBP market, driven by increasing oversupply and portfolio rebalancing arguments, may have led to higher correlation between order flow and volatility and liquidity in the one-month-ahead forward market in 2014. This hypothesis is supported by evidence in Figures 2.4 (b) and 2.2 (a)-(c), suggesting increasing daily trading volume, lower NBP prices and higher price volatility in 2014, and Figure 2.6, indicating decreasing liquidity in the period.

Cumulative response functions showed that an unexpected one-standard-deviation shock to order flow, that is a shock to liquidity demand, increases volatility on average by 0.2 standard deviation. Increased volatility leads to 0.8 standard deviation higher spread. Furthermore, VAR parameter estimates suggested that the response of liquidity to price shocks may exacerbate and perpetuate price volatility, thus generating what Danielsson and Payne (2012) defined "a vicious liquidity/volatility cycle" (p. 802). Together the results in this chapter support the market microstructure theory and, more broadly, the view that trading activity conveys information affecting asset pricing (Merton, 1973; Hasbrouck, 1991). In particular, order flow by reflecting cumulative order imbalances and inventory risk over fixed time intervals allows inference on the process of adjustment of price volatility and liquidity to the information impounded in the trading activity over time. Hence, the microstructure theory from financial markets can be extended to physical markets, in particular to the natural gas market, and helps in understanding the drivers of liquidity.

As a result of the US shale gas revolution, increased volumes of coal came to Europe during 2012-13, coinciding with reduced gas and electricity demand due to the ongoing economic crisis and very low carbon prices in the EU Emissions Trading System. Together these factors led to a sustained gas to coal switch in the UK power sector at that time (Ofgem, 2015) and may explain the decreases in level and variation of the liquidity measures in the period. Moreover, during 2013-14, the NBP hub saw a drop in physical deliveries in favour of the Dutch hub TTF (European Commission, 2015) and a progressive shift of trades from the OTC to exchange-trade markets. In 2014, the premium of oil-linked contracts over hub prices in Continental Europe gave buyers a higher incentive to buy from hubs, in anticipation of greater volumes to be taken at lower oil-indexed prices that followed the drop in the oil prices from July 2014 (Timera-Energy, 2015b). This likely behaviour of market participants together with a gradual exit of investors from the commodities markets, which had been observed since 2013, can explained the observed negative trend in the trading activity despite an overall improvement in liquidity (Tables 2.7 and 2.5, respectively) and might have increased price pressure and volatility, thus contributing to reduce liquidity during 2014. This scenario is consistent with the observed increase in the price impact measure λ_n and in the correlation between order flow and return volatility during 2014 and supports the greater variability of the liquidity measures in the same period.

Nevertheless, the competitiveness of the coal prices has been partially offset by the progressive introduction of the carbon price uplifts in the UK since 2013, which reached £18/tonne in April 2015, and by the reduced share of oil-indexed gas prices in Europe. Thus, one may conjecture increasing natural gas demand in the medium term in UK, particularly after the UK Government cancelled its £1 billion investment in carbon capture and storage technology and restricted coal-fired power plants by 2023, ahead off a full switch off by 2025 (Government of the United Kingdom, 2015). This predicted higher demand and the low level of investment in new flexible gas capacity (i.e. storage capacity, Ofgem (2015)) question future liquidity and price volatility in the UK natural gas market and, more broadly, natural gas security. As argued by Felix et al. (2013), storage operators anticipate market liquidity and take this expectation into account in their operating decisions: the lower the liquidity, the higher the market price, the lower is the storage value. Storage also represents a real option, because it offers the immediate opportunity to trade natural gas or to wait for changing markets conditions, as prescribed by the theory of storage (e.g. Fama and French, 1987, 1988). Thus, lack of liquidity is a constraint for forward trading when storage value and operation are accounted for. Given the positive correlation between liquidity and price volatility, there are strong implications for hedging and inventory management, likewise for energy policy decision making.

Notwithstanding an increase in the liquidity measures during 2014, no significant changes in these measures were observed after the entering into force of REMIT (Table 2.14), thus implying neither deterioration nor improvement in the competitiveness and efficiency of the one-month-ahead NBP forward market following the higher transparency brought by REMIT. However, the measures of spread and price impact indicated higher volatility since REMIT. Furthermore, impulse response functions suggested an increase in the equilibrium response of spread to volatility, which moved from 0.7 standard deviation in the Pre-REMIT period to one standard deviation in the Post-REMIT (Figure 2.13). Although increases in volatility may be reasonably explained by the decrease in the trading activity over the period, it may also reflect changes in the composition of market players. Higher administrative costs may not have directly affected liquidity, but they could have made the market less attractive for financial investors. This would entail higher financing and hedging costs, mostly for small-size energy companies with tiny positions in the market.

As a whole, this analysis highlights how seasonality is critical in energy markets. Liquidity in the one-month-ahead NBP forward market reflects the weather-dependency of the demand for natural gas. Also, the findings demonstrate the importance of price volatility and imbalances that are linked to the fundamental values of demand, supply and inventory in explaining long-term movements in liquidity of natural gas markets. Therefore, factors influencing inventory risk and order imbalances, as well as the behaviour of market participants play an important role in driving liquidity in the one-month-ahead NBP forward market. Although the findings are limited to the share of the market that was analysed, they are consistent with expectations based on previous studies of financial markets, and also with recent reports on energy markets and the behaviour of energy market players (ACER, 2015b; Ofgem, 2015). Nonetheless, the dataset used in this chapter does not discriminate between commercial and financial investors and therefore the impact of REMIT on different types of market participants and trades could not be assessed.

2.8 Conclusions and Further Research

The present chapter contributed to the existing literature on liquidity measurement in energy markets by illustrating the evolution of different dimensions of liquidity in natural gas markets, and the similarities between the natural gas and financial markets. In particular, the key research questions were the following:

1. Are measures of spread and price impact used in financial markets useful to assess different dimensions of liquidity, and their dynamics, in the one-month-ahead NBP forward market?
2. What are the potential drivers of liquidity?
3. Have regulatory changes, and higher transparency, affected the time series behaviour of liquidity?

With respect to the first question, results have shown the usefulness of liquidity measures from financial markets to identify patterns in the different dimensions of liquidity in the one-month-ahead NBP forward market and to measure their relative contribution. In particular, the modified price impact measure λ_n that was adopted in this chapter, and which in contrast to previous literature was estimated in a time-varying fashion, has helped to link trading activity to price returns. In doing so, this measure has enabled the assessment of the depth and resilience of the one-month-ahead NBP forward market in the period studied. Such dimensions of liquidity cannot be captured by the *churn ratio*, which is traditionally used for measuring liquidity in energy markets. Consequently, the measure of price impact λ_n can be valuable to regulators when monitoring market quality, especially given the greater availability of transaction data following the implementation of REMIT.

Drawing from a large share of transactions in the one-month-ahead forward NBP market, the potential drivers of liquidity were identified, thus addressing the second research question posed in this chapter. There are indications that factors influencing price volatility also contribute to explain liquidity dynamics. These observations are of interest to market participants, who consider liquidity as an effective way to spread correct price signals about the fundamental values of demand and supply. Findings are also valuable for independent regulators and energy policy-makers, who are interested in evaluating the efficiency and competitiveness of the market. Given the implications of price volatility for market quality, it is noteworthy to investigate its drivers, which will be the topic of Chapter 3 of this dissertation.

Finally, as for the third question, no significant changes were observed in the liquidity measures following the entering into force of REMIT. However, there was evidence of greater exposure of liquidity to unexpected price changes after REMIT, which might reflect fewer investors in the market, and thus higher transaction costs. Given the implications of higher volatility and transparency for the competitiveness of energy markets, a follow-up study may extend the sample considered in this chapter to further investigate the impact of REMIT on the liquidity dynamics of European energy markets.

Overall, the findings of this chapter supported the extension of the financial market microstructure theory to physical markets and contributed towards understanding dynamics and driving forces of liquidity in energy markets. Higher transactions costs imply lower asset prices and higher rate of returns, which are required to compensate investors for bearing liquidity costs. Transaction costs also affect the ability of a market to offer sufficient opportunities for trading. Higher price volatility and lower liquidity may impede trading, thereby making it easier for a single player to assume a dominant position, with implications for the market competitiveness. In this respect, the observed decrease in the number of transactions per day and the higher variability in their average volumes may signal increasing market concentration in the one-month-ahead NBP forward market. In this case, the participation of smaller energy companies in the trading activity at the NBP hub could be threatened, with important implications for competitiveness, investment decisions and overall market efficiency. Therefore, hub liquidity and, more broadly, hub development may affect competitiveness and thus impact the achievement of a single European natural gas market. Given its relevance for market participants and policy-makers, the assessment of the process towards the integration of European wholesale natural gas markets will be the topic of Chapter 4 of this dissertation.

3

The Volatility of Natural Gas Prices in the United Kingdom Market: Drivers and Spillover Effects**

3.1 Introduction

Natural gas price volatility has become a fundamental input in the decision-making process of European energy companies, especially since environmental concerns have called for greater use of natural gas in the power sector. Higher gas price volatility has induced producers, utilities, generators and industrial consumers to hedge not only against volume risk but also against price risk (Weron, 2007). The greater volatility of natural gas prices relative to the oil prices has been often used to support oil-linked mechanisms in long-term supply contracts for natural gas in Europe (Alterman, 2012). However, as mentioned in Chapter 1 of this dissertation, with the increasing availability of un-contracted spot gas and LNG from the international markets, the premise for oil-indexation is questionable. Gas sold priced at hub grew from 15% in 2005 to 64% in 2015 according to the International Gas Union (International Gas Union, 2016b). Included in this category is spot LNG, which in 2015 accounted for 40% of the total European LNG imports compared to less than 8% in 2005 (International Gas Union, 2016a).

** Extracts of this chapter have been presented at the *Energy and Commodity Finance Conference* (Paris, France. 23-24 June 2016), and the 10th *Energy and Finance Conference* (London, UK. 9-11 September 2015.

Together, the increased exposure to international gas markets and supply/demand dynamics raise concerns on their implications for natural gas price volatility. Therefore, the identification of what may drive natural gas prices volatility has implications for market participants in both the natural gas and electricity markets, and is of interest to policymakers, for whom the efficiency and competitiveness of energy systems are crucial to secure supply and affordability.

Natural gas price volatility is expected to be driven by weather and seasonalities in demand and storage level (Martínez and Torró, 2015), as well as by production costs and demand inelasticities (Mu, 2007; Suenaga et al., 2008; Suenaga and Smith, 2011; Efimova and Serletis, 2014). Since natural gas is an input to power generation, particularly in periods of peak electricity demand (Serletis and Shahmoradi, 2006; Mason and Wilmot, 2014; de Menezes and Houllier, 2016), cross-market effects between natural gas and electricity are expected, as well as between natural gas and coal, since they compete for power generation. Cross-market effects, however, may change over time, in response to shifts in the price competitiveness of different fuel sources, or because of energy policy decisions (Nick and Thoenes, 2014). Therefore, different factors may drive price volatility in the natural gas markets and their contribution is likely to be time-varying.

Though '*The goal of volatility analysis must ultimately be to explain the causes of volatility*' (Engle, 2001, p. 166), little research has provided an economic framework to assess the causes of volatility in European natural gas markets (Nick and Thoenes, 2014) and their relative contributions. The main motivation of this chapter is to investigate volatility spillovers between the UK NBP spot price, and other fuel sources, while allowing for the impact of changes in the fundamental values of demand, supply and inventory. Given the potential links between energy and financial markets and the debate about the contribution of speculative trading in spreading volatility (Singleton, 2013; Cheng and Xiong, 2014), volatility spillovers between NBP and stock markets are also investigated. In order to allow for this investigation, a multivariate GARCH approach is adopted, which is inspired by previous research in other markets (Efimova and Serletis, 2014; Karali and

Ramirez, 2014; Balcilar et al., 2016). Since NBP is the main hub for natural gas trading in Europe, the qualitative results from this chapter should be of interest to other European natural gas markets.

The remainder of this chapter is organised as follows. The literature is reviewed in Section 3.2. Research questions are stated in Section 3.3. In Section 3.4, the methodology is presented. Data are described in Section 3.5. Results are presented in Section 3.6 and discussed in Section 3.7. Section 3.8 concludes, and assesses the study's implications for the literature and future research.

3.2 Literature Review

This chapter follows three streams of literature: 1) The theory of storage, which explains the behaviour of commodity prices based on the fundamental values of demand, supply and inventory; 2) The body of literature concerning co-movements within energy markets; 3) The debate on co-movements between energy and financial markets, and the impact of the "financialisation" of commodity markets on energy price volatilities. These streams are reviewed in what follows.

3.2.1 Theory of storage and role of fundamentals

The theory of storage was developed by economists in the 1930s to explain how fundamentals affect the difference between spot and futures prices, i.e. the spread, and their volatilities. In particular, this theory emphasises the role of inventory in the price determination of storable commodities, such as natural gas. Inventory has an economic value since it permits to manage seasonal and unexpected demand, revisions of the scheduled production and supply disruptions. This value is summarised by the *convenience yield* (Kaldor, 1939; Working, 1948, 1949), which is equivalent to the dividend yield of a stock and represents a timing option attached to the commodity (Brennan, 1958; Telser, 1958). The convenience yield is defined as the difference between the benefits of owing the physical commodity and the cost of storing it. Therefore, it can be either positive or negative, depending upon the season and the level of inventory (Geman, 2005). Furthermore, the convenience yield is the premise to the existence of commodity futures markets, as in the theory of normal backwardation by Keynes, J. M. (1930).

When inventory becomes high, as in the case of natural gas during the injection season in the summer, the convenience yield approaches zero and the spot-futures spread, defined as the difference between futures and spot prices, is positive. This structure of the market is known as *contango*. By contrast, when inventory reduces, during the withdrawal season in the winter, the convenience yield increases and the spread becomes negative. The market is therefore told to be in *backwardation* (Geman, 2005). Contangoed markets usually indicate excess of supply, whilst backwarded markets typically suggest excess of demand. Since marginal production costs are less elastic in the short-term than in the long-term, the spot-futures spread is expected to widen in the short-term (Ng and Pirrong, 1994). On the whole, the theory of storage implies that spot and futures price volatilities increase when the spread widens and that spot price volatility is greater than futures price volatility. Hence, a negative correlation should exist between convenience yield and inventory and, in turn, between inventory and spot price volatility of storable commodities.

The convenience yield has been modelled as a stochastic quantity, thus allowing for different shapes of the forward curves. In their seminal work, Gibson and Schwartz (1990) considered the convenience yield as a mean-reverting exogenous variable, driving the stochastic process of storable commodity spot prices in a 2-factor model. By contrast, Routledge et al. (2000) proposed an equilibrium model where convenience yield, spot prices and futures prices are endogenous and inventory-driven processes. A third approach directly exploited the informational content of the inventory level, as implied by the spot-futures price spread to explain the commodity spot price volatility and the dynamics of the convenience yield. In their influential work, Fama and French (1987) and Fama and French (1988) showed that the impact of unpredicted changes of supply and demand on price volatility depends upon the way inventory transmits shocks to prices through time. Since high inventory levels allow to promptly respond to shocks to the demand and supply, low spot price volatility is expected when inventory is adequate. This implies that futures prices should be less volatile than spot prices when inventory is low, but have similar volatility when inventory is high. Furthermore, given the seasonalities in the demand and supply of commodities, seasonalities are also expected in the convenience yield and thus in the spread and price volatility.

The theory of storage should also imply a long-run relationship between spot and futures prices (Lien and Root, 1999; Root and Lien, 2003), where the spot-futures spread represents the inter-temporal no-arbitrage cost of carry condition between the two price processes. However, in the short-run, spot and futures prices may move differently in response to changes in the fundamental values, as for instance, during turmoil periods (Bessembinder et al., 1995). This implies changes in the adjustment towards the long-run spot-futures relationship (Brenner and Kroner, 1995), which reflect into the price volatilities. Hence, the spot-futures spread is expected to vary over time in response to business cycles, or policy decisions.

The role of the fundamental values of demand, supply and inventory and the implications of the theory of storage for energy commodities were investigated by Geman and Ohana (2009). The authors found greater correlation between natural gas price volatility and inventory in winter, when inventory is below its historical average, than in summer. Using a generalised autoregressive conditional heteroscedastic (GARCH) approach (Bollerslev, 1986; Bollerslev et al., 1988), Mu (2007) showed that in the US market the volatility persistence of natural gas daily prices depends on inventory. The implications of the theory of storage for hedging price risk exposure in natural gas markets were also analysed by Suenaga et al. (2008), who reported strong seasonal variations in the daily NYMEX natural gas futures price volatility and in its persistence, resembling the seasonal pattern of the US natural gas storage level. Seasonality and inventory were found to affect the correlation between spot and futures prices, thus the variance of portfolio returns, with consequence for optimal hedging strategies. Back et al. (2013) further highlighted the importance of accounting for seasonality in commodity prices volatility to improve option valuations.

Brooks et al. (2013) observed seasonalities in the daily spot-futures spread of heating oil, natural gas, crude oil and gasoline traded on the NYMEX, thus supporting the view that the convenience yield varies following seasonal changes of the inventory level. Moreover, in the spirit of Fama and French (1987), the authors showed that spot-futures spread predict subsequent price changes, which supports the theory of storage since a stable relationship between the spot-futures spread and price volatility exists.
As highlighted above, the implications of the theory of storage and the predictive ability of the spot-future spread for price volatility have been investigated in commodity and energy markets. Nonetheless, previous studies on energy markets were mostly focused on the US markets. To the best of our knowledge, the implications of the theory of storage in the context of the evolving European natural gas markets remain to be addressed.

3.2.2 Co-movements within energy markets

The need to provide a reliable assessment of the factors driving energy prices volatility has nourished some research addressing the mechanisms through which price volatility transmits within energy markets. For example, using multivariate BEKK-GARCH models (Engle and Kroner, 1995), Ewing et al. (2002) examined volatility persistence and transmissions in the US energy stock markets. The authors found evidence of price volatility spillovers between natural gas and oil markets and greater persistence of the natural gas stock price volatility, compared to the volatility of oil stock prices. Their findings suggest higher responsiveness of natural gas prices to own shocks relative to oil prices. Using GARCH models, and daily price series from 1990 to the bankruptcy of Enron Corporation in 2001, Pindyck (2004b) observed significant spillovers running from the crude oil market to the natural gas market in the US, but not in the opposite direction. Furthermore, price volatilities were found to fluctuate through the sample, thus affecting the value of oil- and gas-based derivative contracts, such as futures and options. Co-movements between natural gas and electricity prices were investigated by Serletis and Shahmoradi (2006) in the Canadian Alberta's market. Adopting a multivariate GARCH framework and daily data, the authors reported significant volatility transmissions and cointegrating relationships between the two price series during the period 1996-2004, thus suggesting high degree of integration between the two markets.

More recently, multivariate GARCH models were used by Chang et al. (2010) and Jin et al. (2012) to study volatility transmissions in the oil markets, and by Higgs (2009) to analyse electricity markets. In particular, Jin et al. (2012) adopted a BEKK specification and daily futures prices to investigate the information flow within oil markets in the period 2005-11. Daily data and a GARCH-BEKK model were also adopted by Efimova and Serletis (2014) to assess volatility spillovers between crude oil, natural gas, and electricity in the US market over the period 2001-13. The authors found that volatility spillovers were unidirectional from oil to gas and electricity markets, thus suggesting strong dependency of the US energy system and economy on oil in the period. Using a multivariate GARCH-BEKK specification and daily data, Karali and Ramirez (2014) found evidence of changes in volatility transmissions between natural gas and the crude oil markets during the period 1994-2011, which were attributed to macroeconomic events and political turmoil. In particular, the authors emphasised the impact of the 11^{th} September 2001 terroristic attack on the crude oil volatility, which spread across energy markets, thus suggesting that major events and/or business cycles may contribute to energy market integration. Yet, Ramberg and Parsons (2012) highlighted the role of technological breakthroughs and economic factors, such as the development of hydraulic fracturing (fracking) in explaining time-varying correlations between natural gas and crude oil price volatilities in the US. Long-run relationships between oil and natural gas prices were reported by Asche et al. (2006), Villar and Joutz (2006), Panagiotidis and Rutledge (2007) and Asche et al. (2015). Time-varying volatility transmissions were also found between energy and carbon markets (Mjelde and Bessler, 2009; Balcilar et al., 2016), thus highlighting the implications of environmental policy decisions for cross-market correlations and volatility spillovers in energy markets.

Previous findings on price volatility transmissions within energy markets mostly focus on the US markets and reveal time-varying behaviours. The integration of energy markets in Europe has been addressed among others by Bosco et al. (2010), Bunn and Gianfreda (2010), Bencivenga et al. (2011), Bollino et al. (2013) and de Menezes et al. (2016). In general, some integration was observed between buying markets and fuel sources. However, how price volatility transmits within different and evolving European energy markets appears to have been neglected, as well as its implications for the efficiency and competitiveness of natural gas markets in Europe.

3.2.3 Co-movements between energy and financial markets

The high volatility experienced by energy commodities in the last decade has led to a debate on the role of financial trading activity in energy markets. Some research has suggested that energy prices volatility, driven by changes in the fundamental values, has been curbed by the presence of financial investors in energy-related derivatives markets (Irwin and Sanders, 2010). In particular, oil prices have been regarded as strongly related to the fundamentals of demand, supply and inventory (Hamilton, 2009; Kilian, 2009), and the oil price increase during 2007-08 has been attributed to a strong demand from developing countries against a stagnating world production (Hamilton, 2009). However, this reasoning may fail to explain the sharp growth of oil prices that was observed during the first half of 2008, with increases greater than 40% in a six-month period, and prices that peaked at $147 per barrel on a intraday basis in July 2008 (Cheng and Xiong, 2014). Given the difficulties to estimate the strength of the global economy growth at that time, final-goods producers may have interpreted the increasing crude oil futures prices as a signal of future economic expansion, instead of noisy trading nourished by financial investors (Cheng and Xiong, 2014).

Following Gorton and Rouwenhorst (2006), who emphasised the opposite dynamics of commodities and equities during business cycles, financial investors have increased their positions in commodity markets, either to exploit the benefits of diversification during periods of stress in traditional financial markets, or as a way to hedge against inflation. Although in the last fifteen years some research (Stoll and Whaley, 2010; Büyükşahin and

Harris, 2011; Irwin and Sanders, 2012; Fattouh et al., 2013) has failed to find a systematic link between speculative trading, commodity prices and their volatilities, the possibility that financial investors may have contributed to spread risk in commodity markets has been not excluded in other studies (Gilbert, 2010; Tang and Xiong, 2012; Singleton, 2013). Some empirical literature dealing with co-movements between commodity and traditional financial markets reveals a change in correlations between the two markets around the 2007-08 financial crisis. For instance, by adopting a double smooth transition conditional correlation (DSTCC-GARCH) model with weekly data, Silvennoinen and Thorp (2013) showed increasing correlation between equity and commodity markets during the period 1990-2009, thus suggesting great integration between the two markets. This integration would discourage, rather than foster, the use of commodity markets as a refuge during periods of stress in traditional financial markets, as argued by Creti et al. (2013) and Olson et al. (2014), who investigated correlations between commodity and stock markets. Using asymmetric DCC-GARCH, Aboura and Chevallier (2015) observed an increase in the volatility transmissions within bonds, foreign-exchange and commodity markets since the 2007-08 financial crisis. Overall, these results contradict Chong and Miffre (2010), who had observed decreasing correlations between commodities and traditional financial assets during the financial crisis in a multivariate GARCH setting.

Whether and how financial investors may affect commodity markets remains debatable, as highlighted by Cheng and Xiong (2014) and Olson et al. (2014). Nonetheless, whenever equity portfolios are used to replicate the performance of physical-energy price returns (Andriosopoulos and Nomikos, 2014), the correlation between financial assets and commodities is expected to be high, thus questioning whether price volatility transmits between natural gas and financial markets, and what are the implications for the stability of energy sectors in Europe.

3.3 Research Questions

The reviewed literature suggests that natural gas price volatility changes over time, according to seasonality, business cycles, energy policy decisions and trading activity, and in response to volatility transmissions from other energy and financial markets. To date, however, little research has been devoted to investigate the dynamics of European natural gas price volatility after the liberalisation process. In this chapter, the following research questions are addressed in the UK natural gas market, which is a representative of liberalised European natural gas markets (Cummins and Murphy, 2015; European Commission, 2015):

1. What are the implications of the theory of storage in the UK natural gas market? That is, what is the contribution of the fundamental values of demand, supply and inventory in driving price volatility in the UK natural gas market?

2. To what extent does price volatility transmit within the UK natural gas and other energy markets?

3. Does price volatility transmit between natural gas and financial markets in the UK?

Assessing the time-varying features of the natural gas price volatility is worthy of investigation for practitioners, concerned about hedging price risk exposure, and for policy-makers, interested in guaranteeing stability in energy markets. Since, in Chapter 2 of this dissertation, price volatility was found to be correlated with market liquidity, results from this chapter have also implications for liquidity, and consequently for the overall quality of the market. In the next section, the methodological approach, used to address the stated research questions is presented.

3.4 Methodology

3.4.1 Assessing the link between theory of storage and spot-futures spread

In order to investigate the implications of the theory of storage in the UK natural gas market and assess the contribution of fundamental values in driving price volatility: 1) The correlation between inventory and spot-futures spread is investigated, which describes how shocks to demand and supply transmit to prices over time; 2) The cointegrating relationship between spot and futures price series is analysed, and its time-varying behaviour is ascertained.

Association between inventory and spot-futures spread

Let $F_{t,T}$ be the futures price at time t for delivery at time T, and S_t the spot price at time t. According to the theory of storage $F_{t,T} - S_t$, that is the return from a purchase at time t, and a sale at time t of the same amount for delivery at maturity T, equals the interest forgone during the storage period $[T-t]$, i.e. $S_t R_{t,T}$, augmented by the marginal storage cost, $C_{t,T}$, less the marginal convenience yield from holding an additional unit of inventory, $W_{t,T}$, that is:

$$F_{t,T} = S_t[1 + (R_{t,T} + C_{t,T} - W_{t,T})\,(T-t)], \tag{3.1}$$

where $R_{t,T}$ denotes the continuously compounded rate prevailing at date t for maturity T. The quantity

$$s_{t,T} = \frac{F_{t,T} - S_t\,(1 + R_{t,T}\,(T-t))}{S_t}, \tag{3.2}$$

where is $s_{t,T} = (C_{t,T} - W_{t,T})\,(T-t)$, represents the interest-adjusted spread (spread, hereafter). As mentioned above, shocks to demand and supply transmit to prices through time by means of inventory. Following (Fama and French, 1987) and Geman and Ohana (2009), in this chapter 3-, 6-, and 12-month maturities are considered and the interest rate is adjusted accordingly.

The strength of the association between inventory and spread is assessed using non-parametric Spearman rank correlation coefficient, which allows for possible non-linear dependencies between the variables and minimises the effect of extreme values. Given N pairs of observations (X_n, Y_n), the corresponding rank values are separately assigned. For each pair (X_n, Y_n), the difference d_n between the relative rank values is computed, and the coefficient $R = \sum_n^N d_n^2$ is computed. For large samples, the test-statistic is thus defined as $Z = \frac{6R - n(n^2-1)}{n(n+1)\sqrt{n-1}}$, which, under the null hypothesis of correlation, is approximately normally distributed. This analysis is carried out after deseasonalising the time series, and thus focuses on the irregular component of the inventory and spread variables. A sine/cosine function is used to deseasonalise the series, since this type of function has been found to fit the seasonal components of inventory and spread series in commodity markets well (Geman and Ohana, 2009; Symeonidis et al., 2012; Back et al., 2013).

Cointegration between spot and futures prices

Spot and futures energy prices have been found to be stationary and mean-reverting (Elder and Serletis, 2008; Lee et al., 2006; Lee and Lee, 2009). Yet, there is also evidence of non-stationarity and persistence (Maslyuk and Smyth, 2008; Ghoshray and Johnson, 2010; Ozdemir et al., 2013; Barros et al., 2014; Presno et al., 2014). To assess the properties of the natural gas price time series, the Augmented Dickey Fuller (ADF) test (Dickey and Fuller, 1979, 1981), the Phillips and Perron (PP) test (Phillips and Perron, 1988), and the KPSS by Kwiatkowski et al. (1992) are used here. While the ADF and PP tests assess the null hypothesis of non-stationarity against the alternative of stationarity, KPSS tests the opposite.

Unit root tests, however, have low power when the alternative hypothesis is specified in a fractional form (Diebold and Rudebusch, 1991; Lee and Schmidt, 1996). To overcome this issue, in this chapter a fractional integration approach is used, which permits to determine the order of integration d. The process is said to be long memory if $d \leq 1$; if $d \in (0, 0.5)$, the process is long memory but covariance-stationary; if $d \geq 0.5$, the process is non-stationary; finally, the process is mean-reverting if $d < 1$, such that the impact of shocks disappears in the long-term, whilst if $d \geq 1$, shocks are persistent (Baillie, 1996). Since natural gas price series have been found to be fractional integrated at different frequencies (Yaya et al., 2015), a fractional integration approach is here justified. As in Barros et al. (2014), Yaya et al. (2015) and de Menezes and Houllier (2016) the integration of order d, $I(d)$, is modelled as follows:

$$(1-L)^d y_t = u_t, \quad t = \pm 0, 1, 2, ... \tag{3.3}$$

where y_t represents the observed process, $(1-L)^d$ is the fractional difference operator, defined as $(1-L)^d = \sum_{k=0}^{\infty} \frac{\Gamma(k-d)L^k}{\Gamma(-d)\Gamma(k+1)}$, where $\Gamma(\cdot)$ is the Gamma function. The resulting covariance stationary process u_t is thus an $I(0)$ process after differentiation. The order of integration d, which represents the speed of mean-reversion, is estimated through the Exact Local Whittle (ELW) estimator by (Shimotsu and Phillips, 2005) and the semi-parametric two-step Feasible Exact Local Whittle (FELW) estimator (Shimotsu and Phillips, 2006; Shimotsu, 2010). These estimators have been shown to be robust against misspecification (Shimotsu, 2010) and are therefore reliable when assessing fractional integration in energy price series (de Menezes and Houllier, 2016). Fractional cointegrating relationships are assessed between spot and futures price in the UK natural gas market through the Engle-Granger procedure (Granger, 1986; Engle and Granger, 1987). The time series y_t and x_t, that are integrated of order d and b, respectively, are then said to be fractionally cointegrated of order (d, b) if the error correction term, which is defined by their linear combination:

$$\varepsilon_t = y_t - \beta x_t, \tag{3.4}$$

is fractionally integrated of order $d - b$, where $0 < b \leq d$ (Banerjee and Urga, 2005). A rolling procedure is adopted to ascertain time-varying behaviours in the long-run relationship, which may be driven for instance by business cycles or policy decisions. Time windows are of constant size, while the sample period is allowed to change on a rolling basis with constant increments. This procedure, which was introduced by Hansen and

Johansen (1999), has been used, among others, by de Menezes and Houllier (2016) to investigate time-varying price converge within European power markets, and by Nomikos and Pouliasis (2015) to assess time-varying cointegration relationships in petroleum forward curves.

3.4.2 Investigating the link between spot-future spread and price volatility

The measure of spread as defined above is used to assess the extent to which shocks to the demand and supply drive volatility in the UK natural gas spot market. As argued by Ng and Pirrong (1994), spot price return volatility is related to inventory conditions immediately prior to the shock that leads to the return at time t, whereas the spread at time t includes the effects of the shock. Thus, $s_{t-1,T}$ in Eq. (3.2) measures variations in initial demand, supply and inventory conditions. This implies that $s_{t-1,T}$ represents the information that is relevant to capture the effect of shocks to the fundamentals on the spot price return volatility.

In order to investigate price volatility dynamics in the UK natural gas market, GARCH models are used in this chapter, since they have been widely used in previous literature to model volatility in energy markets (e.g. Lin and Tamvakis, 2001; Morana, 2001). In line with previous research (Alizadeh and Nomikos, 2011), the univariate Exponential GARCH (EGARCH, Nelson, 1991) specification is used to model price return volatility. The EGARCH specification has been chosen because it allows for asymmetric responses in both magnitude and sign to shocks, while relaxing non-negativity assumptions on the parameters. The conditional mean and variance equations are augmented by the lagged-squared-spread, in accordance with Ng and Pirrong (1994), who found that the squared value maximises the log-likelihood function when compared with different functions of spread, such as the real value or the absolute value. Following Lee (1994), this specification may be referred to as EGARCH-X model and the following is here adopted:

$$r_t = \alpha_0 + \sum_{p=1}^{P} \alpha_p r_{t-p} + \gamma s^2_{t-1,T} + \epsilon_t, \quad \epsilon_t \mid \mathcal{F}_{t-1} \sim iid(0, \sigma_t^2), \quad t = 1, ..., T \tag{3.5}$$

$$\sigma_t^2 = exp\left(\beta_0 + \sum_{k=1}^{K}\beta_{1,k}\frac{|\epsilon_{t-k}|}{\sigma_{t-k}} + \sum_{q=1}^{Q}\beta_{2,q}\frac{\epsilon_{t-q}}{\sigma_{t-q}} + \sum_{m=1}^{M}\beta_{3,m}\ln\sigma_{1-m}^2 + \lambda s_{t-1,T}^2\right) \qquad (3.6)$$

where r_t is the spot price return at time t, and $s_{t-1,T}$ is the lagged-spread.

In this model, asymmetric ARCH effects in magnitude are captured by the coefficients $\beta_{1,k}$, whilst asymmetric ARCH effects in sign are assessed by the coefficients $\beta_{2,q}$. GARCH effects are inferred from the coefficients $\beta_{3,m}$. The response of returns and their volatility to unpredicted changes in the spread, and thus in the fundamentals, is captured by the coefficients γ and λ in the conditional mean and variance equations, respectively.

The order of lag p of the mean equation in Eq. (3.5) is determined according to SIC. Following Eq. (3.5)-(3.6), the log-likelihood function to be maximised is such as follows:

$$logL_t = -\frac{T}{2}\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\ln\sigma_t^2 - \frac{1}{2}\sum_{t=1}^{T}\frac{\epsilon_t^2}{\sigma_t^2}. \qquad (3.7)$$

The parameters in Eq.(3.5)-(3.6) are estimated via quasi-maximum likelihood (QML), which provides robust estimation of the standard errors, even when the normality assumption in Eq.(3.5) is violated (Bollerslev and Wooldridge, 1992).

3.4.3 Assessing co-movements within markets

GARCH models are used in order to investigate co-movements within markets, since they have been traditionally adopted to assess volatility transmissions in energy markets (e.g. Pindyck, 2004b; Serletis and Shahmoradi, 2006; Chang et al., 2010). In this chapter, the Baba-Engle-Kraft-Kroner (BEKK) model in Engle and Kroner (1995) is used, since it allows for volatility transmissions among different series, as well as volatility persistence within each series (Alexander et al., 2013; Chang et al., 2013). Therefore, this model is suitable when volatility spillovers are the object of interest (Bauwens et al., 2006) and has been also used by e.g. Jin et al. (2012), Efimova and Serletis (2014), and Karali and Ramirez (2014).

Volatility spillovers are analysed by controlling for unpredicted changes in the fundamental values of demand, supply, and inventory, which are captured by the measure of spread above. Asymmetric effects in the conditional variances are allowed, and account for leverage effects, i.e. the presence of a negative correlation between changes in prices and changes in volatility (Black, 1972). A bivariate approach is here adopted, as a parsimonious specification for measuring cross-market effects (Rahman and Serletis, 2012; Chang et al., 2013; Aboura and Chevallier, 2015; Ewing and Malik, 2016).

The conditional mean equation of the BEKK model is described by a vector autoregressive (VAR) model, which allows for price return spillovers (Ling and McAleer, 2003) and is defined as follows:

$$\begin{aligned} \mathbf{r}_t &= \Omega_0 + \Omega_1 \mathbf{r}_{t-1} + ... + \Omega_p \mathbf{r}_{t-p} + \boldsymbol{\epsilon}_t, \quad t = 1, ..., T, \\ \boldsymbol{\epsilon}_t &= H_t^{1/2} \boldsymbol{\eta}_t, \end{aligned} \tag{3.8}$$

where, $\mathbf{r}_t$ and $\boldsymbol{\epsilon}_t$ are the 2-dimensional vectors of the price returns and innovations, respectively. Ω_0 is the 2-dimensional vector of constant terms $\omega_{0,l}$, $l = 1, 2$ and Ω_i, $i = 1, ..., p$ are 2×2 matrices of parameters $\omega_{jl,1}$, $j, l = 1, 2$. The diagonal elements of the Ω_i matrices represent own-mean spillovers, while the off-diagonal elements capture cross-mean spillovers. The order of lag p of the VAR model is determined through SIC. The H_t is the 2×2 conditional variance-covariance matrix, and $\boldsymbol{\eta}_t$ is an independent and identically distributed 2-dimensional zero mean vector error process, such that $E[\boldsymbol{\eta}_t \boldsymbol{\eta}_t^{'}] = \mathbf{I}$, where $\mathbf{I}$ is a 2×2 identity matrix.

In the asymmetric BEKK model, the variance-covariance matrix H_t is defined as follows:

$$H_t = C'C + A'\boldsymbol{\epsilon}_{t-1}\boldsymbol{\epsilon}_{t-1}^{'}A + B'H_{t-1}B + G'\boldsymbol{\epsilon}_{t-1}^{-}\boldsymbol{\epsilon}_{t-1}^{'-}G + K's_{t-1,T}s_{t-1,T}^{'}K + D'x_{t-1,T}x_{t-1,T}^{'}D, \tag{3.9}$$

where A, B, G, K and D are 2×2 matrices of parameters. C is a lower triangular matrix of constants, $c_{i,j}$, $i, j = 1, 2$. A is the matrix of the ARCH parameters $a_{i,j}$: the diagonal elements capture own-shocks, while the off-diagonal elements identify cross-market-shock transmissions; B is the matrix of the GARCH parameters $b_{i,j}$, measuring the own-volatility persistence (diagonal coefficients) and volatility interactions within markets (off-diagonal coefficients). $\boldsymbol{\epsilon}_{t-1}^{-} = \boldsymbol{\epsilon}_{t-1} \circ I_{\boldsymbol{\epsilon}_{t-1}<0}$ is the vector of negative shocks ($\circ$ denotes the Hadamard product, i.e. elementwise or pointwise product) and G is the matrix of parameters $g_{i,j}$ measuring the asymmetric ARCH effects. K is the matrix of coefficients $k_{i,j}$ measuring the effects of the lagged-squared-spread on the conditional variance-covariance process. Finally, D is the matrix of coefficients $d_{i,j}$ of the exogenous variable x, which represents the EU Allowance (EUA) futures contracts and accounts for changes in the carbon-emission market affecting volatility spillovers within natural gas, coal and electricity markets (Balcilar et al., 2016). In the BEKK models, the conditional variance-covariance matrix is positive definite by construction (Silvennoinen and Teräsvirta, 2009).

The bivariate BEKK-GARCH model in Eq. (3.8)-(3.9) is also estimated through QML. The log-likelihood function is given by:

$$logL_t = -\frac{1}{2}\sum_{t=1}^{T}\left[\ln(2\pi) + \ln|H_t| + \boldsymbol{\epsilon}_t' H_t^{-1}\boldsymbol{\epsilon}_t\right]. \tag{3.10}$$

3.5 Data

3.5.1 Database

The data employed in this chapter consist of one-month-ahead daily (Monday-Friday) futures contract prices, traded on the ICE. The UK NBP natural gas price and the main international fuels prices that are used as benchmark in the energy markets are considered, namely: Brent crude oil, Peak Load electricity, CIF ARA coal. These series are available from Eikon-Thomson Reuters. All prices are in US dollar. One-month-ahead futures contracts are used here as proxy of the spot prices (e.g. Geman and Ohana, 2009), therefore in the remainder of this chapter, spot prices refer to one-month-ahead prices. Futures contract specifications and expiration dates are provided by ICE. For each contract, rollover effects are accounted for (ICE, 2015a) and time series are aligned based on the NBP contracts, which have the nearest rolling date.

Electricity prices are for Peak Load since these are applicable to flexible higher marginal cost plants (Bunn, 2004) and are generally more volatile than base load prices. Therefore, they are more suitable to assess price volatility transmissions between natural gas and electricity markets, when compared to base load prices.

The FTSE100 index is a proxy for the European financial market over the full sample and represents the 100 largest and most actively traded companies on the London Stock Exchange. Two out of the five largest FTSE100 companies are in the oil and gas sector (BP and Royal Dutch Shell A), which is currently the sector with the highest capitalisation (13.80%) on the FTSE100 total net market capitalisation (FTSE Russell, 2015).

The sample covers the period 2 January 2000 - 22 May 2015. Data for the electricity and coal futures contracts are available since 14 September 2004 and 17 July 2006, respectively. This chapter also relies on official statistics of natural gas inventory, which are available through the UK's national transmission operator National Grid (National Grid, 2015). The data corresponds to the end-of-day inventory level and storage capacity, covering the period 4 January 2010 - 22 May 2015.

The sample includes the most recent boom-and-bust cycles in commodity markets and should enable the identification of changes in volatility transmissions over varying market conditions. Still, there is need for handling outliers and unusual observations, as described below.

Outliers treatment of the price series

There is no consensus on what the threshold should be in order for an observation to be defined as outlier (Janczura et al., 2013). Following Clewlow and Strickland (2000), Cartea and Figueroa (2005) and Weron (2008), in this chapter the threshold is defined by three standard deviations of the absolute price returns and a recursive filtering technique is adopted to identify and replace outliers. Prices with absolute returns exceeding the threshold are extracted and substituted with a 'normal value'. The threshold value of the remaining series from the previous filtering is calculated; returns which are greater than the new threshold are discarded and replaced. The process is repeated until no further outliers can be filtered. Inspired by Bierbrauer et al. (2007) and Janczura et al. (2013), the median of the prices within the same year and month is used to smooth outliers in order to preserve dynamics in the price time series, which may reflect seasonal patterns and market conditions. Convergence was achieved after 6 iterations in the Brent crude oil price series and after 7 iterations in the FTSE100 series; 7 and 9 iterations were required to achieve convergence in the NBP and electricity price series, respectively, whilst convergence in the CIF ARA coal series was achieved after 13 iterations.

The price return series are computed from one-month-ahead futures prices with the same delivery. For each series, the first return immediately following the last trading day is removed. Therefore, the computed returns are free of roll-over and seasonal effects (Weron, 2007; Ohana, 2010). A preliminary analysis of the treated price series and of the inventory data is presented below.

3.5.2 Preliminary data analysis

Price data

The daily spot energy and stock prices are shown in Figure 3.1. Over the full sample, an increase in the NBP prices can be observed, which is mostly evident during the period 2000-06, characterised by (i) a gradual depletion of the UK natural reserves and lack of replacement; (ii) stronger demand of natural gas for electricity generation compared to the previous decade; (iii) increasing Brent crude oil and oil product prices, which at that time were a key component of the natural gas prices in Europe (Alterman, 2012). On the whole, energy prices appear to follow a trend until the first half of 2008. Some mean-reversion can be noticed in the electricity time series and to a lesser extent in the other energy price time series. Positive trends are also evident in the FTSE100 time series during the period 2003-07 and in the aftermath of the 2007-08 financial downturn.

Daily energy price and stock returns are depicted in Figure 3.2. Overall, the figure suggests greater volatility in the NBP market, when compared to the other markets. This is mostly evident in the period 2009-10 and from 2014 onwards. On the whole, nonlinear relationships in the energy and financial squared-returns can be inferred from Figure 3.2, which indicate clusterings.

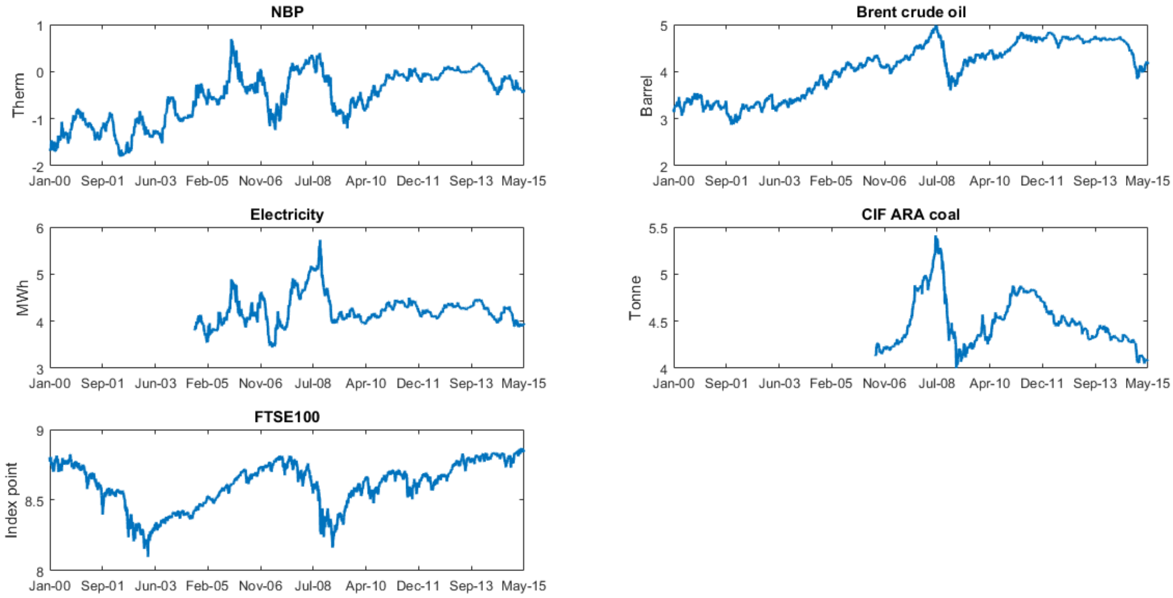


Figure 3.1: Daily spot energy and stock prices (US dollar)

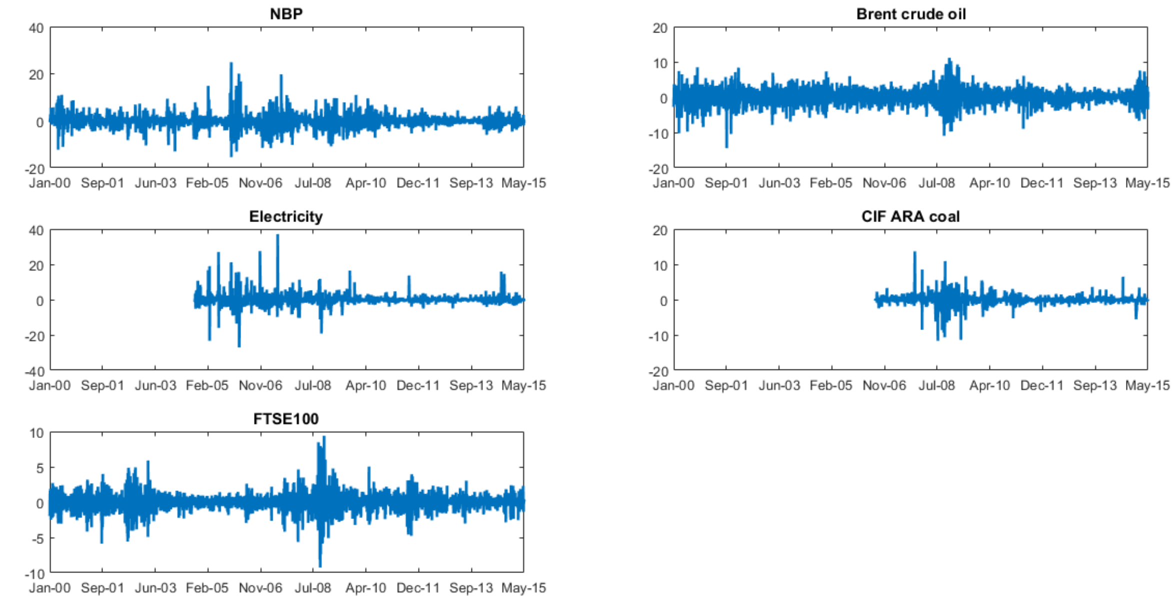


Figure 3.2: Daily energy price and stock returns

Descriptive statistics of the daily energy price and stock returns are presented in Table 3.1. The first four moments (Mean, Std.Dev., Skewness and Kurtosis) are shown in rows two to five; median, minimum and maximum values are given in rows six to eight, respectively. Rows nine, ten and eleven report the p-values of the Jarque-Bera statistics for the assumption of normal distribution, Ljung-Box statistics for the null hypothesis of serial independence and ARCH tests for the null hypothesis of homoscedasticity, respectively. These statistics are computed at the 20^{th} order of lags, which accounts for a time window spanning one month. The number of observations, along with the percentage of the identified outliers, are reported in rows twelve and thirteen.

Non-parametric pairwise signed tests for equality of the medians suggest that the NBP and electricity price returns are lower than the other energy and financial returns. The standard deviations indicate greater volatility in the NBP, Brent crude oil and electricity series when compared to the CIF ARA coal and FTSE100 series, as implied by pairwise F-test statistics. On the whole, price returns have skewed and leptokurtic distributions, even after filtering, which reject normality, as confirmed by the Jarque-Bera tests. ARCH effects are not rejected at 1% significance level in all series, whilst there is evidence of serial independence when the Brent crude oil series is considered. Overall, data cleaning results in a percentage of smoothed observations ranging from a minimum of 2.2% (Brent crude oil) to a maximum of 7.1% (CIF ARA coal) of the available sample.

Table 3.1: Descriptive statistics of the daily energy price and stock returns

	NBP	Brent crude oil	Electricity	CIF ARA coal	FTSE100
Mean	-0.123	-0.002	-0.113	0.010	-0.004
St.Dev.	1.933	1.854	1.521	0.641	0.939
Skewness	0.089	-0.100	-0.149	0.000	-0.164
Kurtosis	3.91	3.44	4.94	5.31	3.722
Median	-0.124	0.025	-0.103	0.000	0.049
Min	-7.04	-6.20	-6.23	-2.71	-3.195
Max	7.54	5.874	6.08	2.85	3.088
Jarque-Bera	0.001***	0.001***	0.001***	0.001***	0.001***
ARCH (20)	0.000***	0.000***	0.000***	0.000***	0.000***
Ljung-Box (20)	0.000***	0.455	0.000***	0.001***	0.011**
Obs.	3,334	3,334	2,315	1,917	3,334
Outliers (%)	4.65	2.20	5.83	7.09	3.39

Note: ***, ** and * denote significance at 1%, 5% and 10%, respectively.

As argued, for instance, by Pindyck and Rubinfeld (1994) and Cartea and Figueroa (2005), the observed serial dependence suggests seasonality in the series, which is a well-recognised feature of the energy prices (Pindyck, 2004a; Weron, 2007; Mu, 2007; Geman and Ohana, 2009; Back et al., 2013). Seasonality can provide an explanation for the observed higher volatility of the NBP, Brent crude oil and electricity prices, and may be driven by weather-dependent demand or supply functions (Fama and French, 1987; Koopman et al., 2007; Geman and Ohana, 2009; Symeonidis et al., 2012), as observed in the NBP price returns in Chapter 2 of this dissertation.

In order to assess seasonalities, in Table 3.2 the descriptive statistics of the energy price and stock returns computed on a monthly basis are reported. Higher volatility is observed in the NBP, electricity and CIF ARA coal returns during the winter compared to the summer, as implied by pairwise F-test statistics for the equal standard deviations (row three). Compared to the results from the full sample in Table 3.1, Jarque-Bera, ARCH and Ljung-Box tests performed on a monthly basis suggest seasonal components in the price return distributions. In particular, ARCH effects appear to be significant during winter season and this is mostly evident in the NBP, electricity, and CIF ARA coal series. Notably, the NBP prices show lower returns in December compared to the other months.

As observed in Chapter 2 of this dissertation, December is characterised by historically lower month-on-month traded volumes. This circumstance, coupled with the positive correlation between trading activity and price changes suggested by results in Chapter 2, may explain the observed lower NBP price returns in December relative to the rest of the year. On the whole, the preliminary analysis of the return series supports the adoption of GARCH models to investigate volatility dynamics and spillover effects within the markets here considered. The reported statistics also support the use of the EGARCH specification, which allows for asymmetric responses to shocks and thus permits to model the NBP price volatility dependence on the state of the market.

Table 3.2: Descriptive statistics of the energy price and stock returns by month

NBP	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Mean	-0.198	-0.088	-0.019	-0.288	-0.070	-0.140	-0.080	-0.101	-0.092	-0.158	-0.056	-0.385
St.Dev.	2.729	2.181	1.804	1.904	1.989	1.738	1.563	1.782	1.815	1.861	1.979	2.349
Skewness	0.096	-0.126	0.134	0.110	-0.037	0.053	0.004	-0.096	-0.281	-0.016	0.194	0.247
Kurtosis	3.27	3.72	3.37	3.36	3.842	3.50	3.495	3.39	3.520	3.12	3.398	3.58
Median	-0.299	0.159	-0.254	-0.327	0.069	-0.188	-0.192	-0.055	-0.046	-0.253	-0.032	-0.536
Min	-7.95	-6.49	-4.67	-5.25	-5.751	-4.89	-4.184	-4.64	-5.436	-5.12	-5.252	-6.84
Max	8.05	5.846	5.27	5.21	5.854	5.14	4.405	5.00	5.258	4.68	5.915	7.00
Jarque-Bera	0.468	0.037**	0.229	0.326	0.023**	0.190	0.193	0.306	0.035**	0.500	0.136	0.043**
ARCH (20)	0.002***	0.160	0.793	0.008***	0.068*	0.000***	0.013**	0.710	0.080*	0.038**	0.016**	0.151
Ljung-Box (20)	0.000***	0.200	0.980	0.652	0.155	0.392	0.402	0.684	0.576	0.023**	0.001***	0.846
Obs.	292	275	299	268	273	271	287	273	275	289	276	256
Brent crude oil												
Mean	-0.035	0.244	-0.028	0.077	0.088	0.058	0.015	0.121	-0.266	-0.027	-0.047	-0.235
St.Dev.	1.945	1.898	1.964	1.763	1.822	1.804	1.580	1.671	1.830	1.834	1.984	2.088
Skewness	0.096	0.029	-0.177	-0.239	-0.016	-0.135	-0.092	-0.063	-0.066	-0.029	-0.026	-0.315
Kurtosis	3.75	3.39	3.64	3.19	2.853	3.13	3.353	3.18	3.391	3.03	3.531	3.37
Median	-0.067	0.235	-0.048	0.134	0.125	0.144	0.083	0.082	-0.206	-0.179	-0.133	-0.026
Min	-5.53	-5.34	-5.54	-4.95	-4.397	-5.10	-4.529	-4.91	-5.476	-5.13	-5.876	-6.20
Max	5.62	5.611	5.87	4.86	4.897	5.36	4.281	4.95	4.624	4.83	5.282	5.04
Jarque-Bera	0.029**	0.373	0.036**	0.188	0.500	0.500	0.346	0.500	0.335	0.500	0.159	0.052*
ARCH (20)	0.444	0.246	0.001***	0.452	0.316	0.092*	0.001***	0.593	0.121	0.305	0.124	0.022**
Ljung-Box (20)	0.282	0.209	0.684	0.224	0.137	0.378	0.472	0.208	0.944	0.564	0.031**	0.082*
Obs.	292	275	299	268	273	271	287	273	275	289	276	256
Electricity												
Mean	-0.771	-0.093	0.092	-0.107	0.009	-0.013	-0.033	0.081	-0.068	0.175	-0.354	-0.109
St.Dev.	2.151	1.898	1.600	1.381	1.639	1.619	1.812	1.191	1.698	1.586	2.119	1.790
Skewness	-0.134	0.260	0.005	0.072	0.405	-0.034	0.131	-0.016	-0.054	0.150	0.016	0.345
Kurtosis	3.28	3.96	3.21	3.32	3.775	4.19	3.671	3.10	3.551	4.02	4.121	4.02
Median	-0.800	-0.063	0.063	-0.196	-0.050	-0.030	0.000	0.159	-0.084	-0.020	-0.260	-0.262
Min	-6.20	-5.32	-4.46	-3.82	-4.237	-4.82	-5.407	-3.19	-4.912	-4.76	-6.206	-4.92
Max	5.68	5.659	4.57	3.89	4.856	4.59	5.078	3.19	4.646	4.65	6.091	5.33
Jarque-Bera	0.500	0.018**	0.500	0.500	0.016**	0.013**	0.095*	0.500	0.225	0.015**	0.013**	0.010**
ARCH (20)	0.024**	0.721	0.467	0.592	0.210	0.013**	0.000***	0.362	0.002***	0.055*	0.000***	0.002***
Ljung-Box (20)	0.058*	0.583	0.609	0.751	0.194	0.329	0.166	0.835	0.017**	0.828	0.000***	0.743
Obs.	200	189	205	185	185	182	191	182	194	210	203	189
CIF ARA coal												
Mean	-0.153	0.042	-0.009	0.015	-0.030	0.030	0.040	0.011	0.017	0.090	0.054	0.006
St.Dev.	0.959	0.738	0.757	0.799	0.562	0.749	0.369	0.514	0.506	0.509	0.471	0.512
Skewness	0.016	0.161	-0.284	0.225	0.218	0.283	0.114	-0.032	0.477	0.006	0.165	0.352
Kurtosis	4.40	4.41	4.29	3.93	3.729	3.37	3.696	3.47	4.006	3.67	3.189	4.16
Median	-0.120	0.000	0.000	0.000	0.000	0.000	0.069	0.000	-0.054	0.035	0.000	-0.070
Min	-2.71	-2.16	-2.25	-2.13	-1.536	-1.82	-1.070	-1.21	-1.311	-1.43	-1.152	-1.47
Max	2.85	2.091	2.13	2.34	1.570	2.04	1.023	1.41	1.460	1.46	1.351	1.51
Jarque-Bera	0.008***	0.008***	0.007***	0.035**	0.076*	0.187	0.116	0.407	0.008***	0.148	0.500	0.011**
ARCH (20)	0.040**	0.327	0.302	0.352	0.747	0.004***	0.158	0.566	0.020**	0.632	0.538	0.031**
Ljung-Box (20)	0.043**	0.088*	0.797	0.926	0.085*	0.050**	0.819	0.642	0.731	0.903	0.675	0.222
Obs.	165	155	167	152	150	144	163	163	165	174	165	154
FTSE100												
Mean	-0.053	0.004	-0.004	0.058	-0.049	-0.123	0.006	0.016	-0.046	0.063	0.003	0.080
St.Dev.	0.855	0.931	0.854	0.911	1.092	0.917	0.927	0.870	1.039	0.999	0.972	0.879
Skewness	-0.116	-0.147	-0.109	-0.248	-0.518	-0.158	-0.041	-0.146	-0.041	0.107	-0.088	-0.358
Kurtosis	3.45	4.00	3.23	3.45	3.674	3.32	3.405	3.66	3.864	3.59	3.684	3.98
Median	0.003	0.021	0.025	0.097	0.092	-0.048	0.027	0.074	-0.040	0.049	0.042	0.126
Min	-2.50	-2.73	-2.56	-2.65	-3.195	-2.64	-2.741	-2.47	-3.032	-2.87	-2.745	-2.52
Max	2.38	2.710	2.50	2.44	2.644	2.68	2.600	2.49	3.088	2.85	2.827	2.41
Jarque-Bera	0.176	0.008***	0.500	0.068*	0.003***	0.273	0.321	0.048**	0.020**	0.078*	0.050**	0.005***
ARCH (20)	0.002***	0.001***	0.058*	0.135	0.022**	0.628	0.002***	0.051*	0.000***	0.000***	0.005***	0.055*
Ljung-Box (20)	0.842	0.230	0.608	0.043**	0.781	0.826	0.471	0.399	0.220	0.168	0.092*	0.579
Obs.	292	275	299	268	273	271	287	273	275	289	276	256

Note: ***, ** and * denote significance at 1%, 5% and 10%, respectively.

Inventory data

The UK natural gas inventory level is depicted in Figure 3.3. Not surprisingly, a strong yearly seasonal path is observed, which reflects natural gas demand. Inventory level reduces in the winter withdrawal seasons and increases in the summer, when injections take place. In Figure 3.4, the UK natural gas remaining storage capacity is considered. It represents the difference between the total available storage capacity and the level of inventory at each point in time. This variable is a proxy for scarcity (Ng and Pirrong, 1994): the lower the remaining capacity, the lower the scarcity, the higher is the inventory level with respect to the total available storage capacity. Therefore the remaining storage capacity variable is used here to assess the implications of the theory of storage in the UK natural gas market.

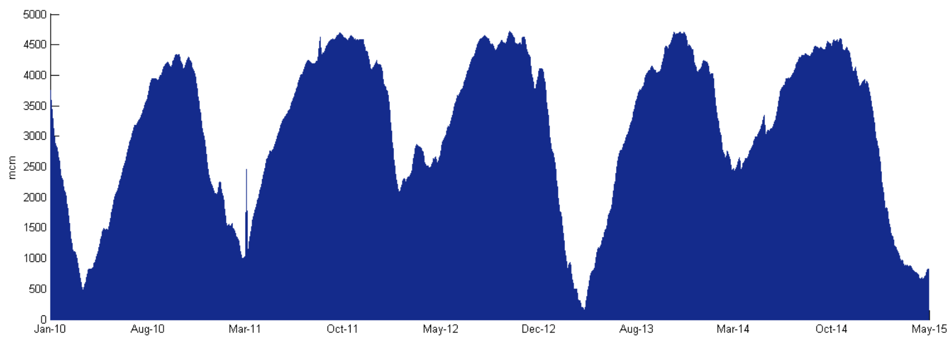


Figure 3.3: Natural gas inventory level in the UK

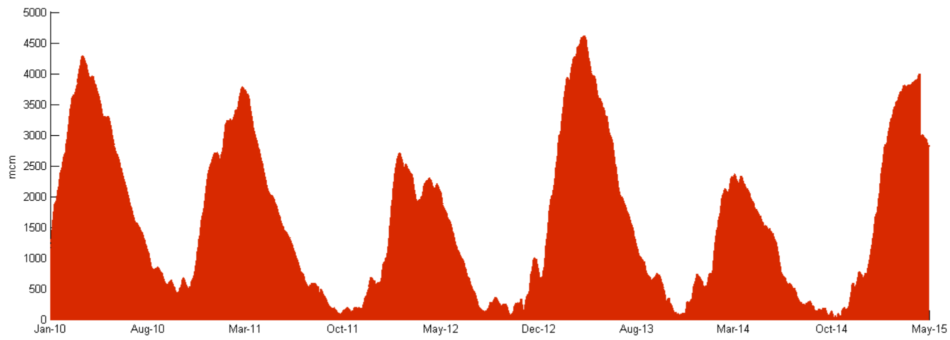


Figure 3.4: UK natural gas remaining storage capacity

3.6 Empirical Results

3.6.1 The link between theory of storage and spot-futures spread in the UK natural gas market

On the association between inventory and spot-futures spread

The spread, as defined in Eq.(3.2) and computed at different maturities is shown in Figure 3.5. A strong yearly seasonal pattern can be observed. The spread is found to be negative in the winter and positive in the summer, thus resembling natural gas demand seasonalities. Furthermore, it is negative when inventory reduces and the convenience yield is high. By contrast, when inventory increases and the convenience yield approaches zero, the spread is positive, which is in line with the theory of storage. Consequently, negative spreads suggest excess of demand, whilst positive spreads indicate excess of supply. In the UK natural gas market, these dynamics are more evident in the period 2000-10, in particular in 2006, following a fire at the storage facility Rough in February (ICIS, 2006). The time-varying behaviour of the spread is mostly observed when the 3- and 6-month maturity are considered (Figure 3.5 top and mid plots) relative to the 12-month maturity (Figure 3.5 bottom plot), which is also affected by missing data before November 2006.

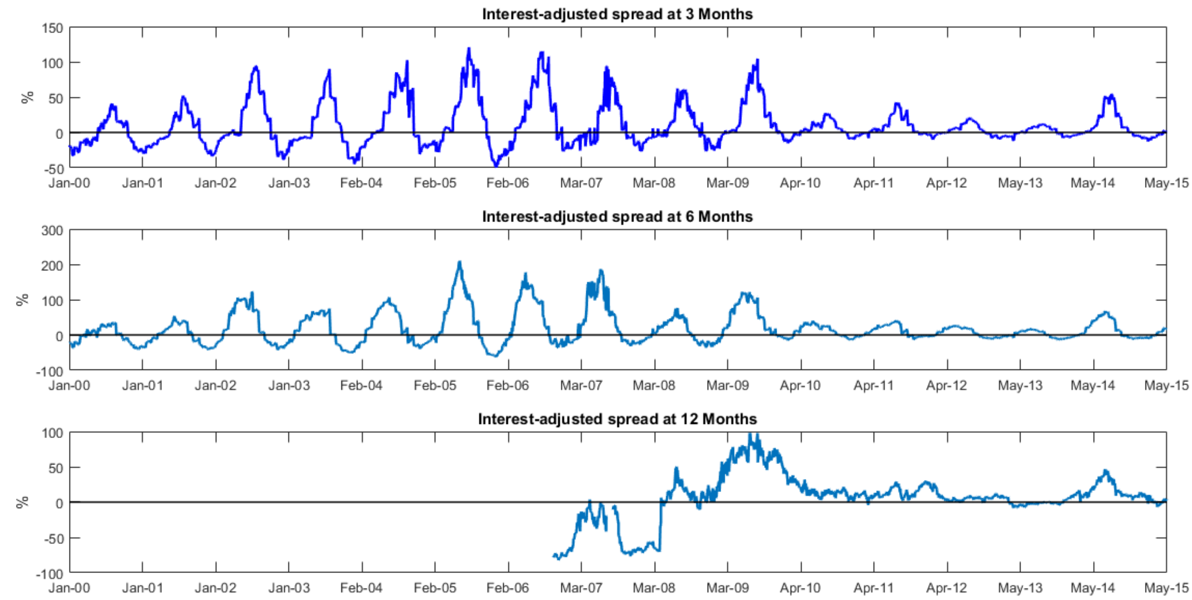


Figure 3.5: Spread at different maturities

Figure 3.6 shows the traded volume of the NBP futures contracts at different maturities (4-, 7- and 13-month, which are the contracts used to compute the spreads in Figure 3.5). As shown in the bottom of the figure, the 13-month-ahead NBP futures contracts are only recorded from November 2006 onwards, when trading activity is observed.

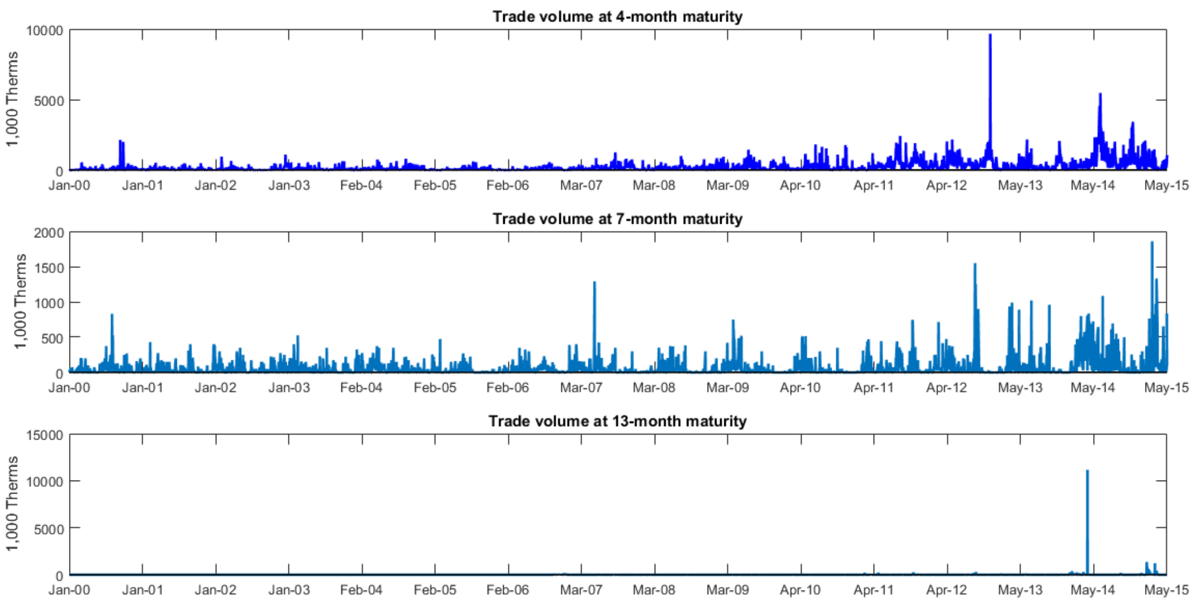


Figure 3.6: Traded volume at different maturities

Descriptive statistics of the spread at different maturities are presented in Table 3.3. Rows two to five show the first four moments (Mean, Std.Dev., Skewness and Kurtosis); median, minimum and maximum values are given in rows six to eight, respectively. Rows nine to eleven report the p-values of the Jarque-Bera statistics for the normality assumption, Ljung-Box statistics for the null hypothesis of serial independence, and ARCH tests for the null hypothesis of homoscedasticity, respectively. These statistics have been computed at the 20^{th} order of lags, which accounts for a one-month time window. The number of observations is given in row twelve.

Mean and median values are positive and significantly different from zero, thus suggesting that on average the UK natural gas market was oversupplied in the sample period. Furthermore, higher volatility is found in the 6-month maturity spread at 5% of significance compared to the 3-month series, as implied by pairwise F-test statistics for equal variances. This suggests greater uncertainty on the fundamental values of supply, demand and inventory in the medium- and long-term, as predicted by the theory of storage. Nonetheless, lower volatility is observed in the 12-month maturity spread series relative to the 6-month maturity. This may be explained with the reduced sample period, which is characterised by lower variability, as observed in Figure 3.5. On the whole, the spread series are asymmetrically and leptokurtic distributed; not surprisingly, Jarque-Bera statistics reject the normality assumption at 1% significance level. Finally, serial dependence and heteroscedasticity are significant at 1% level in all series.

Table 3.3: Descriptive statistics of the spread at different maturities (%)

	3-month	6-month	12-month
Mean	9.935	18.03	6.182
St.Dev.	29.30	44.79	33.23
Skewness	1.197	1.281	-0.551
Kurtosis	4.33	4.70	4.16
Median	1.525	6.561	8.083
Min	-48.34	-61.06	-82.30
Max	131.5	210.4	98.00
Jarque-Bera	0.001***	0.001***	0.001***
ARCH (20)	0.000***	0.000***	0.000***
Ljung-Box (20)	0.000***	0.000***	0.000***
Obs.	3,519	3,519	1,776

Note: ***, ** and * denote significance at 1%, 5% and 10%, respectively.

Seasonal dynamics are investigated in the spread series. Summer and winter medians and standard deviations of the spread at different maturities are reported in Table 3.4, along with the p-value of their pairwise equality tests (non-parametric signed test and F-test, respectively). Summer and winter seasons have been split according to the ICE UK natural gas futures specifications: April-September (summer); October-March (winter) (ICE, 2015c).

In line with the theory of storage, spread at 3- and 6-month maturity are positive in the summer and negative in the winter, thus corroborating Figure 3.5. Pairwise F-tests indicate greater volatility in the summer than in the winter, which is consistent across maturities. This would be in contradiction with the theory of storage, predicting higher volatility in the winter, when inventory reduces. Nonetheless, spread volatilities might reflect portfolio adjustments to the annual storage cycle. As observed in Chapter 2 of this dissertation, summer months are characterised by storage injection, as well as by significant volumes of gas flowing from the UK towards North-West European markets to refill Continental Europe storage facilities. The additional demand from the Continental European markets implies high price pressure in the UK market, also in consideration of its limited storage capacity (Heather, 2010; Koenig, 2012). This would require frequent portfolio rebalancing, thus providing a possible explanation for the observed higher volatility of the spread during the summer, when the UK market is more exposed to arbitrage opportunities with Continental Europe and traded volumes are higher compared to physical delivery, as inferred from the *churn ratio* dynamics in Chapter 2.

Table 3.4: Summer and winter medians and standard deviations of the spread at different maturities

	Median			St. Dev.		
	Summer	Winter	Equality test	Summer	Winter	Equality test
3-month	18.58	-6.72	0.00***	29.88	15.65	0.00***
6-month	36.78	-10.09	0.00***	42.52	16.83	0.00***
12-month	10.08	9.99	0.00***	27.43	17.05	0.00***
Obs. (3-, 6-month)	1,739	1,780				
Obs (12 -month)	942	1,023				

Note: ***, ** and * denote significance at 1%, 5% and 10%, respectively.

In table 3.5, the Spearman's correlations between scarcity and adjusted spread at different maturities are reported, which allow to assess the strength of the association between inventory and spread. Correlations are computed on the seasonally adjusted series and indicate that the spread is a decreasing function of scarcity, in line with some previous empirical evidence (Ng and Pirrong, 1994; Symeonidis et al., 2012). This pattern is mostly evident when the 3-month maturity spread is considered.

Table 3.5: Spearman correlations between scarcity and adjusted spread at different maturities

	3-month	6-month	12-month
Jan	0.256***	-0.283***	0.065
Feb	-0.097	-0.153	0.083
Mar	-0.271***	0.233**	0.200**
Apr	-0.427***	-0.104	0.298***
May	-0.055	-0.143	-0.143
Jun	-0.105	0.21**	-0.228**
Jul	-0.005	-0.314***	-0.162
Aug	0.209**	0.325***	0.199*
Sep	0.178*	-0.073	0.046
Oct	0.050	0.050	-0.118
Nov	0.363***	0.238**	-0.354***
Dec	-0.269***	0.063	-0.201**

Note: ***, ** and * denote significance at 1%, 5% and 10%, respectively.

On the whole, results support the theory of storage implications in the UK natural gas market. A close link is observed between spread and supply/demand dynamics, which implies that the fundamental values contribute to drive natural gas prices. Yet, when the NBP futures market is considered, the different levels of trading activity across maturities raise concerns about the degree of liquidity of this market for longer deliveries (above six months). This issue has been also observed by Martínez and Torró (2015) in different European forward markets for natural gas.

The high correlation between 3-month maturity spread and inventory would be in line with some rolling hedging strategies used in matures natural gas markets, such the UK and Continental Europe markets, to maximise storage value (de Jong, 2016). Faster cycle storage facilities, with deliverability rate up to 3 months, are used to balance injection and withdrawal patterns in response to market conditions in the UK market (Timera-Energy, 2014, 2016). Therefore, it is reasonable to assume that market players adjust their positions in the futures market accordingly, thus providing an explanation for the observed greater correlation between inventory and 3-month maturity spread relative to the spread at longer maturities considered here. Consequently, in the remainder of this chapter, the

3-month maturity spread will be used to investigate the relationship between fundamental values and natural gas price volatility in the UK market. In the next subsection, the time series properties of the NBP spot and 4-month-ahead futures prices, which constitute the 3-month maturity spread, are assessed and their cointegrating relationship investigated.

Cointegration between spot and futures prices in the UK natural gas market

Results from the integration analysis of the NBP spot and 4-month-ahead futures prices are presented in Table 3.6. Columns two to four address the presence of unit root in the series and show ADF, PP and KPSS tests. Estimates of the order of integration d, obtained through ELW and FELW statistics, are reported in columns five and six, along with their 95% confidence interval (in squared brackets).

The NBP spot price time series (row two) is found to be integrated of order one at 1% of significance, according to the ADF and the KPSS tests. By contrast, the PP test suggests stationarity at 10% level. When the 4-month-ahead futures price time series is considered (row three of Table 3.6), the hypothesis of unit root is supported by the PP and KPSS tests at 1% level of significance, but is rejected by the ADF test at the same level of significance. Still, the coefficients ds from the ELW and FELW statistics, which provide an estimate of the integration order, are all included in the interval (0.9, 1.1), thus supporting the non-stationarity of the series. Therefore, the fractional cointegrating analysis is here justified to address cointegration between NBP spot and futures price series.

Table 3.6: Order of integration of NBP spot and 4-month-ahead futures prices

	ADF	PP	KPSS	ELW	FELW	Obs.
Spot	-2.987	-3.184*	0.242***	0.926 [0.897; 0.956]	0.991 [0.962; 1.020]	3,519
4-month-ahead futures	-4.726***	-2.812	0.369***	0.989 [0.959; 1.018]	1.054 [1.024; 1.083]	3,519

Note: ***, ** and * denote significance at 1%, 5% and 10%, respectively.

The time-varying order of integration d of the NBP spot and 4-month-ahead futures series, and of their error correction term in Eq. (3.4) are shown in the top of Figure 3.7. In the bottom of the figure, periods of cointegration, identified by 1, and periods of no cointegration, 0, are depicted. The rolling procedure assumes constant increments of 1 day on rolling windows of size 1,200, corresponding to 5 years, and with a bandwidth m=550. The plots have been smoothed by using a HP filter (Hodrick and Prescott, 1997) with smoothing parameter $\lambda = 100$.

Although time-varying, the order of integration of the spot and futures price time series ranges between 0.9 and 1.15, which is consistent with the estimates obtained in the full sample (Table 3.6). This supports the non-stationarity of the NBP price processes during the period 2000-15 and appears to be in line with Geman (2007), who highlighted a change in the properties of the natural gas price series from mean-reverting to random walk since 2000, likewise with some previous research (Maslyuk and Smyth, 2008; Ghoshray and Johnson, 2010; Ozdemir et al., 2013; Barros et al., 2014; Presno et al., 2014). Yet, the estimated order of integration of the error correction term is not sufficiently lower than those of the spot and futures prices, in order for them to be cointegrated. The hypothesis of cointegration is therefore rejected in the period 2000-10 and for most of the period 2011-15, as shown in the bottom of Figure 3.7. Although there is lack of evidence of cointegration between NBP spot and futures prices, the time series processes and their co-movements appear to be time-variant, in particular when the period from 2011 onwards is considered.

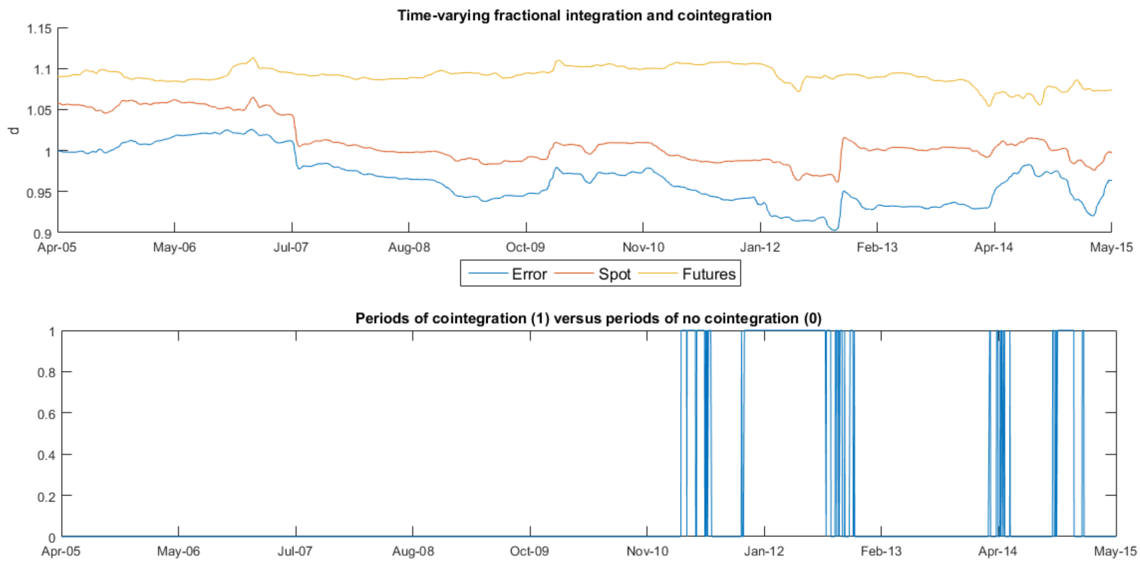


Figure 3.7: Time-varying fractional integration and cointegration

Descriptive statistics of the time-varying order of integration d of the spot, futures and error correction term series are reported in Table 3.7. For each series, the first four moments are shown in rows two to five (Mean, Std.Dev., Skewness and Kurtosis, respectively); median, minimum and maximum values are given in rows six to eight; the number of observations in the sample is reported in row nine. The mean values of the spot and futures series are consistent with the ELW and FELW statistics in the full sample (Table 3.6, columns five and six). The order of integration of the error term is on average 0.964, with a 95% confidence interval of [0.921; 1.006], thus confirming the non-stationarity of the process.

Table 3.7: Descriptive statistics of the order of integration d of the NBP spot and 4-month-ahead futures prices, and of their error correction term

	Spot	4-month-ahead futures	error correction term
Mean	1.010 [0.968; 1.051]	1.091[1.049; 1.083]	0.964 [0.921; 1.006]
St.Dev.	0.026	0.011	0.030
Skewness	0.776	-0.773	0.189
Kurtosis	2.480	3.846	2.014
Median	1.003	1.092	0.965
Min	0.956	1.054	0.433
Max	1.066	1.116	0.981
Obs.	2,320	2,320	2,320

On the whole, results indicate that the strength of the association between NBP spot prices, and NBP futures prices at short maturities (up to 4-month-ahead) is time-variant. This implies that convenience yield is not constant over time, and spot and futures prices are differently affected by business cycles and shocks to fundamental values, reflecting on their spread and long-run relationship. Therefore, the results are in line with predictions based on the theory of storage, and support the reasoning that spread carries information about price volatility. In the next subsection, the contribution of the spread in explaining the spot price volatility in the UK natural gas market is thus assessed.

3.6.2 The link between spread and price volatility in the UK natural gas spot market

Parameter estimates and key residual diagnostic tests of the EGARCH-X model in Eq. (3.5)-(3.6) of the NBP price returns are presented in Table 3.8. In the mean equation, the autoregressive coefficient is positive and significant (α_1 in row three of the table). Therefore, positive (negative) price returns are more likely to be followed by positive (negative) price returns, thus indicating high persistence and clustered behaviours in the NBP spot market. Yet, NBP price returns appear to be independent of the lagged-squared-spread (coefficient γ in row four).

Parameter estimates of the conditional variance suggest significant high persistence (0.977) in the NBP price return volatility, as measured by the GARCH coefficient $\beta_{3,1}$ (row eight of Table 3.8). This implies that shocks to the UK natural gas market tend to die out slowly. Asymmetric ARCH effects in magnitude, as measured by the coefficient $\beta_{1,1}$ (row six of Table 3.8), are significant and indicate that greater (above average magnitude) shocks have higher impact on the NBP spot price volatility compared to smaller shocks. Asymmetric ARCH effects in sign ($\beta_{2,1}$ in row seven of the table) are also significant and suggest that negative shocks tend to reduce the NBP price volatility, while positive shocks tend to increase volatility in subsequent periods. Finally, the coefficient of the lagged-squared-spread (λ in row nine) is significant and implies that a positive correlation exists between changes in the fundamental values and price volatility in the UK natural gas market. The NBP spot price volatility increases when spread becomes wider and this occurs at an increasing rate, as implied by the quadratic function. ARCH and Ljung-Box tests (rows eleven and twelve in Table 3.8) fail to reject the hypotheses of homoscedasticity and serial independence at 1% of significance and 5^{th} order of lags, thus the model is well-specified. Similar to the findings by Ng and Pirrong (1994), the lagged-squared-spread is found to maximise the log-likelihood (in row ten of the table) compared to the real and absolute spreads[1].

[1] The log-likelihood functions of the model estimated with the real and absolute spreads were found to be -6644 and -6642, respectively.

Table 3.8: Parameter estimates and residual diagnostic tests of the EGARCH-X model of the NBP price returns

		Coeff.	Std.Er.	z-stat
Mean	α_0	-0.0492	0.0345	-1.427
	α_1	0.108***	0.017	6.253
	γ	-0.230	0.160	-0.150
Variance	β_0	-0.127***	0.010	-12.87
	$\beta_{1,1}$	0.197***	0.014	13.81
	$\beta_{2,1}$	0.019***	0.007	2.530
	$\beta_{3,1}$	0.977***	0.004	234.5
	λ	0.024***	0.011	2.251
Residual Diagnostics	Log-likelihood	-6641		
	ARCH (5)	1.184		
	Ljung-Box (5)	5.966		

Note: ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively.

On the whole, results support the theory of storage. In particular, fundamental values are found to determine the NBP spot-futures spread. Results from the EGARCH-X estimation indicate that fundamentals represent primary drivers of the NBP spot price volatility and contribute to explain its time-varying behaviour. The implications of these results for market players and policy-makers are discussed in Section 3.7.

The significance of lagged variance and lagged-squared-error terms in the EGARCH-X model specification does not exclude that other factors may contribute to the dynamics of the UK natural gas price volatility and its persistence. Therefore, in the next section, volatility transmissions within energy markets, as well as between natural gas and financial markets are investigated.

3.6.3 On co-movements of markets

Volatility transmissions within energy markets

Parameter estimates and key residual diagnostic tests of the bivariate asymmetric VAR-BEKK models in Eq. (3.8)-(3.9) are presented in Table 3.9. Results of the BEKK model addressing co-movements between NBP and Brent crude oil price returns are shown in columns three and four. Columns five and six report the parameter estimates of the BEKK model for NBP and electricity. Finally, results of the model for the NBP and CIF ARA coal price returns are presented in columns seven and eight. Mean equations follow a VAR(1) process, selected based on residual diagnostics and SIC. Standard errors of the parameter estimates are shown in parentheses.

Overall, the estimates of the mean equations indicate significant and positive serial dependence in the price return series, as inferred by the coefficients $\omega_{1,1}$ (row five). This suggests that energy price returns are characterised by high persistence and clustering, which can be driven by cyclical events that affect energy markets in the same way and simultaneously, such as economic cycles or policy decisions.

Positive and significant cross-market price spillovers are also observed in the NBP-Electricity model (see coefficients $\omega_{2,1}$ in row seven of Table 3.9). Parameter estimates indicate that a 10% increase in the NBP price raises the next period's electricity price by 0.42%, whilst an 10% upward change in the electricity price increases NBP by 0.05% in the next period. Parameter estimates of the variance equations indicate high persistence (above 0.55) in the price volatilities, as inferred through the GARCH coefficients b_{11} and b_{22} (rows sixteen and nineteen of Table 3.9, respectively). ARCH effects are also significant (see coefficients a_{11} and a_{22} in rows twelve and fifteen of the table) and imply that shocks to the energy prices die out slowly. On the whole, persistence and long memory affect price volatility in the UK energy markets, which is in line with previous findings in North American energy markets (Efimova and Serletis, 2014; Karali and Ramirez, 2014).

Asymmetric ARCH effects are observed in the NBP-Brent crude oil BEKK model (see coefficient g_{22} in row twenty-three of Table 3.9). They suggest that negative shocks lead to subsequent increased volatility of the Brent price. This is in line with previous literature investigating asymmetric effects in the crude oil markets (Wang and Wu, 2012). Asymmetric effects are also observed in the electricity price volatility, as inferred by the coefficient g_{22} in the NBP-Electricity model.

BEKK parameter estimates indicate volatility spillovers. Shocks to the NBP prices are found to be correlated with previous shocks to the Brent crude oil prices (see coefficients

a_{21} in row fourteen of Table 3.9), whilst greater price volatility of the electricity and CIF ARA coal prices leads to subsequent higher NBP price volatility (see coefficients b_{21} in row eighteen). Therefore, volatility transmissions exist within energy markets and drive the NBP price volatility.

The coefficients of spread (k_{11} and k_{22} in rows twenty-four and twenty-seven of Table 3.9) are significant in the NBP-Brent crude oil model and highlight the contribution of the natural gas fundamental values to price volatility in the NBP market.

Carbon price coefficients (d_{11} and d_{12} in rows twenty-eight and twenty-nine) are significant in the NBP-Electricity model and suggest that the EUA scheme affects volatility transmissions between the UK natural gas and electricity markets. Overall, the Ljung-Box statistics fail to reject the hypothesis of serial independence at 1% level of significance and 5^{th} order of lags (see row thirty-four of Table 3.9). The hypothesis of homoscedasticity is rejected at 5% level (see ARCH test in row thirty-five of the table), thus suggesting that the residuals of Eq. (3.8) are asymmetrically distributed, as confirmed by their skewness and kurtosis.

Together, results indicate significant co-movements, which are mostly observed between the NBP and electricity markets. This finding is partially in line with evidence from the US energy sector as reported by Efimova and Serletis (2014). The authors observed price volatility transmissions running from the natural gas to the electricity markets, but not in the reverse direction. By contrast, results in this chapter indicate cross-market effects running in both directions.

Table 3.9: Parameter estimates and residual diagnostic tests of the bivariate asymmetric VAR-BEKK models of NBP and other energy markets

Model		NBP-Brent crude oil		NBP-Electricity		NBP-CIF ARA coal	
		NBP	Brent	NBP	Electricity	NBP	CIF ARA
Mean	ω_0	-0.122***	0.000	-0.164***	-0.086**	-0.142***	0.009
		(0.035)	(0.0002)	0.043	(0.037)	(0.046)	(0.019)
	$\omega_{1,1}$	0.109***	-0.026	0.050**	0.071**	0.049**	0.115***
		(0.021)	(0.019)	(0.029)	(0.030)	(0.028)	(0.031)
	$\omega_{2,1}$	0.021	0.010	0.005*	0.042*	0.097	0.008
		(0.021)	(0.018)	(0.025)	(0.025)	(0.083)	(0.008)
Variance	c_{11}	1.449***	(0.131)	1.476***	(0.074)	1.283***	(0.06)
	c_{12}	0.153***	(0.035)	1.146***	(0.061)	0.140***	(0.003)
	c_{22}	1.475***	(0.104)	0.198***	(0.036)	-0.459***	(0.049)
	a_{11}	0.205***	(0.021)	0.310***	(0.059)	0.266***	(0.083)
	a_{12}	-0.027	(0.029)	-0.166***	(0.078)	0.019	(0.054)
	a_{21}	-0.054***	(0.028)	-0.032	(0.051)	0.027	(0.017)
	a_{22}	0.188***	(0.048)	0.344***	(0.037)	0249***	(0.092)
	b_{11}	0.611***	(0.084)	0.713***	(0.028)	0.662***	(0.040)
	b_{12}	-0.006***	(0.003)	-0.011	(0.044)	0.021	(0.068)
	b_{21}	-0.012	(0.009)	-0.101***	(0.025)	-0.063**	(0.030)
	b_{22}	0.555***	(0.054)	0.693***	(0.050)	0.579***	(0.074)
	g_{11}	0.120	(0.072)	0.086	(0.068)	-0.026	(0.044)
	g_{12}	-0.020	(0.013)	-0.058	(0.087)	0.048	(0.109)
	g_{21}	-0.004	(0.002)	-0.008	(0.047)	-0.010	(0.022)
	g_{22}	0.365***	(0.050)	0.174*	(0.091)	-0.011	(0.045)
	k_{11}	0.100***	(0.031)	0.101	(0.070)	0.015	(0026)
	k_{12}	-0.001	(0.001)	-0.001	(0.003)	0.001	(0.006)
	k_{21}	-0.001	(0.001)	-0.001	(0.003)	-0.001	(0.002)
	k_{22}	0.101***	(0.033)	0.101	(0.012)	-0.003	(0.011)
	d_{11}			-0.004**	(0.002)	0.066	(0.104)
	d_{12}			0.012***	(0.002)	0.048	(0.109)
	d_{21}			0.006	(0.014)	-0.010	(0.022)
	d_{22}			0.003	(0.012)	-0.011	(0.045)
Residual Diagnostics	Skewness	0.007	-0.0839	0.009	0.035	0.035	0.062
	Kurtosis	3.67	3.4	3.605	3.843	3.584	5.008
	Ljung-Box (5)	3.305	8.292	4.531	8.722	5.374	2.483
	ARCH (5)	16.03**	38.82**	83.86**	28.79**	67.47**	20.11**

Note: ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively.

Figure 3.8 shows the conditional correlations based on the BEKK models. Over the period 2000-15, the correlation between the NBP and Brent crude series is on average 0.07 (Figure 3.8 top plot), with standard deviation of 0.05. This correlation reduces in the period 2008-13, following the economic downturn and increases after the oil prices collapse, in the last quarter of 2014. Correlation between the NBP end electricity series is on average 0.63 over the period 2005-15 (Figure 3.8 middle plot), with standard deviation of 0.21. This correlation is higher from 2010 onwards, compared to the previous period, when less variability is also observed. Finally, the correlation between the NBP and CIF ARA series, in the bottom of Figure 3.8, is on average 0.08 (with standard deviation of 0.07) during the period 2006-15.

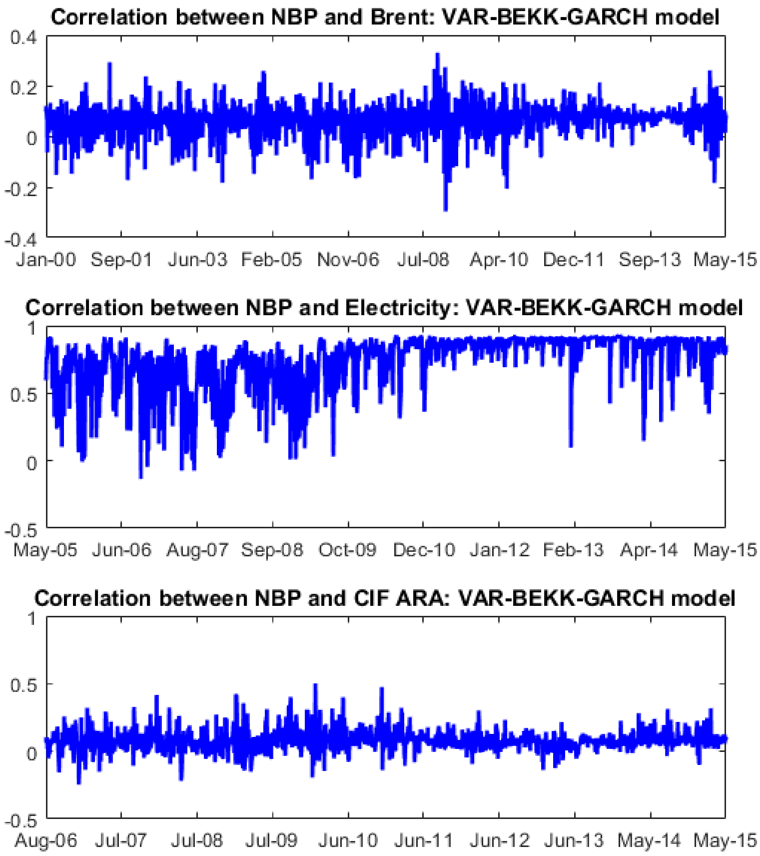


Figure 3.8: Conditional correlations between the NBP and other energy price returns

Overall, results support co-movements within energy markets, which are mostly noticeable when the NBP and electricity series are considered. This suggests high integration between these two markets. Furthermore, correlations highlight the time-varying feature of the links between energy markets, which respond to changes in market conditions. In Section 3.7, these results are discussed, and their implications for market players and policy-makers highlighted. The next subsection investigates co-movements between natural gas and financial markets.

Co-movements between UK natural gas and financial markets

Parameter estimates and residual diagnostic tests of the bivariate asymmetric VAR-BEKK model in Eq. (3.8)-(3.9) for NBP and FTSE100 are presented in Table 3.10. Mean equations are estimated based on a VAR(1) process, following residual diagnostics and SIC. Standard errors of the parameter estimates are reported in parentheses.

Parameter estimates of the mean equations indicate significant serial dependence in both price return series, thus of opposite sign (see coefficients $\omega_{1,1}$ in row five of Table 3.10). Significant cross-market price spillovers are observed in the FTSE100 equation, as shown by the coefficient $\omega_{2,1}$ in row seven and column three of Table 3.10, and imply that a 10% increase in the NBP price reduces the next period's FTSE100 price by 0.14%.

Parameter estimates of the variance equation indicate higher persistence of the NBP price volatility relative to the FTSE100, as inferred by the coefficients b_{11}=0.678 and b_{22}=0.152. Similarly, ARCH effects are more evident in the NBP series (coefficient a_{11}= 0.391) than in the FTSE100 series (coefficient a_{22}=0.163).

Price volatility spillovers are observed between the NBP and FTSE100 markets, which are inferred from the coefficients a_{21}=0.008 and b_{12}=0.010. They imply that shocks to FTSE100 transmit to the NBP market (at 10% significance level) and higher volatility in the NBP market leads to a more volatile FTSE100 in the following period (at 1% significance level).

Asymmetric effects are observed in both NBP and FTSE100 markets, as inferred through the coefficients g_{11}=0.237 and g_{22}=0.173. These effects suggest that negative own-shocks lead to subsequent increased volatility in the markets. Asymmetric cross-market effects are also significant (g_{12}=0.011) and indicate that negative shocks in the NBP market drive higher volatility in the FTSE100 market.

These results support the hypothesis of volatility spillovers between natural gas and financial markets, after considering the impact of fundamental values, as proxied by the lagged-squared-spread and inferred by the coefficients k_{11}=0.103 and k_{12}=0.001. Residual diagnostics of Eq. (3.8) suggest serial independence, as implied by the Ljung-Box statistics at 5^{th} order of lags. ARCH tests fail to reject the hypothesis of heteroscedasticity at 5% level of significance, thus suggesting that the residuals are asymmetrically and leptokurtic distributed, as confirmed by the skewness and kurtosis statistics.

Table 3.10: Parameter estimates and diagnostic tests of the bivariate asymmetric VAR-BEKK of NBP and FTSE100

		NBP-FTSE100	
Mean	ω_0	-0.122***	-0.005
		(0.035)	(0.016)
	$\omega_{1,1}$	0.115***	-0.034*
		(0.021)	(0.019)
	$\omega_{2,1}$	-0.018	-0.014*
		(0.038)	(0.008)
Variance	c_{11}	1.186***	(0.081)
	c_{12}	0.006	(0.005)
	c_{22}	-0.895***	(0.015)
	a_{11}	0.391***	(0.031)
	a_{12}	-0.046	(0.039)
	a_{21}	0.008*	(0.004)
	a_{22}	0.163***	(0.068)
	b_{11}	0.678***	(0.042)
	b_{12}	0.010**	(0.005)
	b_{21}	0.002	(0.002)
	b_{22}	0.152***	(0.056)
	g_{11}	0.237***	(0.061)
	g_{12}	0.011***	(0.002)
	g_{21}	-0.330	(0.025)
	g_{22}	0.173**	(0.103)
	k_{11}	0.103***	(0.033)
	k_{12}	0.001***	(0.0004)
	k_{21}	0.001	(0.001)
	k_{22}	0.183	(0.054)
Residual Diagnostics	Skewness	0.026	-0.166
	Kurtosis	3.647	3.718
	Ljung-Box (5)	4.072	5.782
	ARCH test (5)	40.38**	20.79**

Note: ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively.

Figure 3.9 depicts the correlation between the NBP and FTSE100 series estimated by the BEKK model. Over the period 2000-15, this correlation is on average 0.012, with standard deviation of 0.065. Higher correlation is observed during the period 2008-10, in the aftermath of 2007-08 financial crisis, relative to the previous period. Correlation then reduces from 2011 onwards.

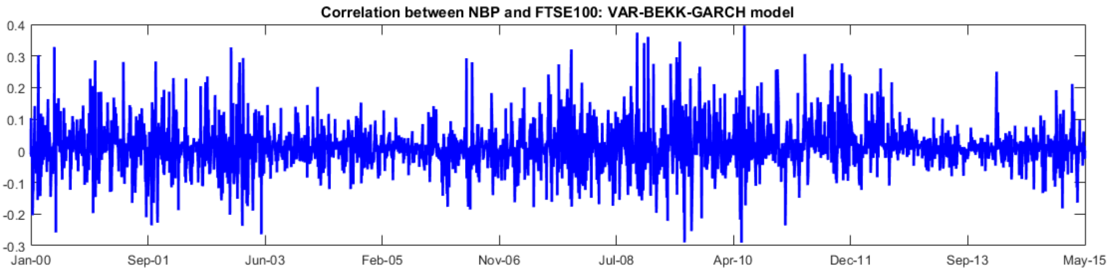


Figure 3.9: Conditional correlations between the NBP and FTSE100 price returns

All in all, results imply co-movements between NBP and FTSE100 markets, which are time-varying and appear to be driven by market conditions. The next section discusses these results and their main implications for researchers, market participants and policy-makers[2].

3.7 Discussion

In line with the theory of storage (Brennan, 1958; Telser, 1958) and following the approach in Fama and French (1987), in this chapter the NBP spot-futures price spread was used to assess the impact of unpredicted changes in the fundamental values of supply, demand and inventory on the volatility of the UK natural gas spot prices, as proxied by one-month-ahead futures prices. Consistent with the theoretical expectations (Fama and French, 1987; Ng and Pirrong, 1994), the spot-futures spread was found to be decreasing functions of scarcity. This link was mostly observed when the 3-month maturity spread was considered. The correlation between inventory and spread was particularly evident

[2] Asymmetric dynamic conditional correlation (ADCC) models were also estimated to investigate co–movements within energy markets, as well as between natural gas and financial markets. Results from the ADCC specification were consistent with evidence from the BEKK specification when the correlations between NBP, and electricity and CIF ARA coal were considered. Differences between the two specifications were observed when the correlations between NBP, and Brent crude oil and FTSE100 were addressed. Nonetheless, this chapter focuses on volatility spillovers, and thus the BEKK specification is more suitable. The ADCC is described in Appendix A of this chapter, where parameter estimates (Tables A.1 and A.2) and dynamic conditional correlations (Figures A.1 and A.2) are also reported.

during the winter (Table 3.5). This implies that storage capacity constraints make spot-futures spread more sensitive to inventory withdrawals, which is in line with conclusions from previous research (Fama and French, 1987; Symeonidis et al., 2012; Gorton et al., 2013). Yet, the greater volatility of the spread in the summer compared to the winter (Table 3.4) contradicts these results, as well as the theoretical expectations of higher spread volatility in winter than in summer (Ng and Pirrong, 1994; Geman and Ohana, 2009). As mentioned above, the summer season is characterised by high arbitrage opportunities between the UK and Continental Europe markets for the storage refill, and consequent high financial trading activity to rebalance portfolios, which was also suggested by the *churn ratio* in Figure 2.1. Given the positive correlation between trading activity and volatility observed in Chapter 2 and the annual storage cycle, it becomes plausible to expect greater spread volatility in the summer than in the winter. This expectation would be further supported by the positive correlation between spread and scarcity observed in August and September, i.e. before the end of the injection season (Table 3.5).

A reduction in the UK net exports to Continental Europe during the summer was observed since 2010 (Department for Business, Energy and Industrial Strategy, 2015), which may have pressurised storage capacity and thus summer spot prices in the UK. This reduction may have followed the decline of the natural gas demand for power generation in Europe as a consequence of (i) declining electricity consumption; (ii) strong renewable sources penetration; (iii) higher competitiveness of coal prices compared to gas prices; (iv) and low Emission Trading Scheme (ETS) price, which have caused gas-to-coal switch in the UK, as well as in Continental European markets (European Commission, 2013, 2014). These factors may further explain the increased spread volatility in the summer and to the lower seasonality that was observed in the spread series from 2010 onwards. These factors would also explain the observed increasing level and variability of the traded volume of the 4-month ahead futures contracts (Figure 3.6), as a consequence of portfolios rebalancing. Although the relationship between inventory and risk premium is ambiguous (Brooks et al., 2013; Gorton et al., 2013), the implications of the theory of storage may entail a decline of the risk premium on the UK natural gas market during the sample period. In the presence of high inventory level and convenience yield approaching zero, inventory holders move their stock from the present to the future, and the spot-futures spread is mainly determined by the cost of storage (Gorton et al., 2013). Since 2010, this spread decreased and the distance between backwardation and contango states narrowed (Figure 3.6). Consequently, traders may have adjusted their positions according to changes in the expected futures prices, which may have led to the observed increase in the traded volume. This would be in line with findings from previous research (Alizadeh and Tamvakis, 2016), which suggests that trading activity in energy futures markets can be explained by the spot-futures spread, which reflects market conditions and sentiment. Therefore, results in this chapter indicate a change in hedging and investment strategies in the UK natural gas market during the sample period.

A change in the adjustment towards the long-run relationship between NBP spot and futures prices was also found in this chapter, which is in contradiction with some previous literature (Lien and Root, 1999). Spot and futures prices are expected to respond differently to changes in the fundamental values (Bessembinder et al., 1995; Brenner and Kroner, 1995), which would justify the time-varying magnitudes of the spread that were observed in this chapter. Results also indicated that from 2010 onwards NBP futures prices evolved towards spot prices, thus eroding some intertemporal arbitrage opportunities. This is supported by the time-varying cointegration analysis, which indicated an increase in the frequency of periods of cointegration since 2010, and is consistent with a reduction in the risk premium in the UK natural gas market. Overall, these results have implications for the hypothesis of market efficiency and price discovery in the UK natural gas market, suggesting that futures prices are unbiased predictors of spot prices at maturity (Dwyer and Wallace, 1992) and influence the predictability of the NBP market.

Results indicate that unpredicted changes in the fundamental values can be observed through the spot-futures spread and drive price volatility dynamics, as suggested by the EGARCH-X parameter estimates. This is in line with theoretical expectations based on the theory of storage. NBP spot price changes and their volatility were found to be correlated to the lagged-squared-spread, thus indicating a non-linear relationship between price volatility and convenience yield. In addition, since the spread was found to be seasonal and affected by seasonal volatility, it can be inferred that the NBP spot price volatility is also driven by seasonality in demand. This supports the theory of storage predictions and add to the empirical evidence from Chapter 2 of this dissertation (Table 2.11). Together, the implications of the theory of storage in the UK natural gas market, assessed in this chapter, allow for generalisations of previous research on price volatility dynamics in natural gas markets, where seasonal effects were accounted for through dummy variables (Mu, 2007), deterministic (trigonometric) functions (Benth and Benth, 2007; Geman and Ohana, 2009; Martínez and Torró, 2015), or inventory level (Geman and Ohana, 2009; Symeonidis et al., 2012), while considering movements in the spot-futures relationship that reflect unexpected shocks to the fundamentals. This consistency in findings is relevant when evaluating hedging strategies and option pricing based on the spot-futures relationship.

The explanatory power of the lagged-squared-spread did not exclude the presence of further drivers of price volatility in the UK natural gas market. Parameter estimates of the VAR-BEKK models implied significant correlations between the NBP spot prices volatility, and the electricity and CIF ARA coal prices volatility. High correlation has been observed between NBP and electricity price volatilities, highlighting the importance of natural gas prices in setting electricity marginal costs in the UK market (Ofgem, 2016). Significant although low correlation was observed between NBP and CIF ARA coal prices, reasonably driven by declining electricity demand in the period, which may have increased the competition between gas- and coal-fired plants for the marginal power generation during peak-load periods. These co-movements between natural gas and coal prices would support fuel substitution effects in the power sector and are in line with previous research on European energy markets integration (Bosco et al., 2010; Bunn and Gianfreda, 2010; Bencivenga et al., 2011; Bollino et al., 2013; de Menezes et al., 2016). However, compared to previous studies on volatility transmissions within energy markets (Efimova and Serletis, 2014; Karali and Ramirez, 2014; Balcilar et al., 2016), the present study addressed the time-variation of the volatility transmissions, thus allowing for some inferences on the market conditions and policy decisions that might have driven energy markets towards higher or lower integration.

Results suggest growing correlation between the NBP and electricity prices since 2011 (Figure 3.8). The drop in the international coal price observed since 2011 (Figure 3.1) and the excess of natural gas supply in European markets (European Commission, 2013) might have reduced the ability of the UK natural gas market to absorb increasing volume of gas thus inducing volatility in the NBP spot market. Nonetheless, the availability of cheap LNG from the international markets and the following drop in the NBP spot prices may have eroded the competitive advantage of coal over gas in the power sector (European Commission, 2013). These factors, coupled with the growth of electricity generation from renewable sources in the UK (103% in the period 2012-15 according to the renewable statistics of the Department for Business, Energy and Industrial Strategy, 2016) and low ETS prices may have increased the exposure of NBP spot price to changes in the coal and electricity prices, thus fostering integration between natural gas and power markets.

It is noticeable that on April 2013, the UK Government introduced a Carbon Price Floor (CPF), thus pushing ETS prices up. The uplift created by the CPF almost doubled in April 2014, from *£*4.94 to *£*9.55 per tonne of CO_2 and reached £18 per tonne in April 2015. It was then capped at a maximum of £18 from 2016-17 until 2019-20. The main intent of the CPF was to foster investments in low carbon generation, as the Climate Change Act 2008 (Parliament of the United Kingdom, 2008) established a target for the UK to reduce its emissions by 50% on 1990 levels by 2025 and 80% by 2050. Furthermore, as mentioned in Chapter 2 of this dissertation, the UK Government restricted coal-fired generation by 2023, ahead of a full switch off by 2025 (Government of the United Kingdom, 2015). Since gas-fired plants lead the marginal wholesale power prices in the UK (Ofgem, 2016), these policy decisions will imply shifts from coal to gas in the UK in the coming decade and increasing integration between the UK natural gas and power sectors. In addition, higher volatility may be expected in the NBP spot market given the increases in intermittent renewable sources and the carbon market, with implications for the stability and competitiveness of the natural gas market.

Time-varying co-movements between NBP and Brent crude oil prices were confirmed by the estimated correlations, and were mostly evident from 2011 onwards. As described in Chapter 1 of this dissertation, traditionally oil and spot gas prices have been correlated in Europe, due to the oil-indexation in the long-term contracts and the flexibility component of the ToP volumes. This correlation is supported by volatility transmissions entailed by the VAR-BEKK parameter estimates and is in line with previous research (Asche et al., 2006; Panagiotidis and Rutledge, 2007; Asche et al., 2015). Nonetheless, there is also evidence that gas hub prices are increasingly driven by flexible sources of supply, such as un-contracted LNG available on the international markets, long-term contract volumes not subject to ToP obligations, direct hub sales of upstream producers (Timera-Energy, 2016). These factors and the excess of natural gas supply in the UK market may have smoothed the traditional relationship between NBP and Brent crude oil prices, and consequently the exposure of natural gas markets to volatility in the oil markets. This would explain the decreased correlation between the two price series observed during 2012-13, when European natural gas markets were in excess of supply. It would also explain the increasing correlation observed from the end of 2014 onwards, when the drop in the international oil prices made the flexible component of the ToP volumes more competitive relative to NBP spot prices. As mentioned in Chapter 2 of this dissertation, starting from 2014, the premium of oil-linked contracts over hub prices gave buyers an incentive to buy from the spot market. However, the oil price collapse in July 2014 resulted in a downward pressure on European hub prices in anticipation of lower oil-indexed gas prices over the first half of 2015 (oil-indexation is typically set using the weighted average of a basket of oil products over a three-month period, with a six- to nine-month time lag (Platts, 2016)). Overall, these results are in line with Asche et al. (2015), who argued that the link between natural gas and oil prices in the UK is weaker during high and stable oil prices, and stronger in time of low and more volatile oil prices. However, results in this chapter suggest the importance of accounting for the dynamics of natural gas supply and demand in the internal market, as indicated by the significance of the spread, and the exposure to international gas markets. These factors and the anticipated growing integration between natural and power sectors may further foster gas-on-gas competition in European natural gas markets (Chapter 1), and thus reduce the traditional correlation between natural gas and crude oil prices, even in times of low and more volatile oil prices.

A time-varying correlation was also found between NBP and FTSE100 prices. In particular, this correlation was observed to increase in the period 2007-11, during the most recent financial crisis and in its aftermath, which is in line with some previous research (Creti et al., 2013; Silvennoinen and Thorp, 2013; Olson et al., 2014; Aboura and Chevallier, 2015), but in contradiction with Chong and Miffre (2010). Results thus would support the flight-to-quality effect in the period, highlighted by Creti et al. (2013), according to which financial investors may have used commodity derivatives as safer investment instruments during the financial turmoil. This is in line with Gorton and Rouwenhorst (2006), in the view that investors may have exploited the benefits of commodity diversification in periods of financial stress. In fact, an inspection of constituents and market-capitalisation weights of the FTSE100 indicate that the overall weight of the oil and gas and mining sectors was 24% in 2007, before the financial crisis, and 34.5% in 2011, compared to 28% and 15% of the banking sector before and after the financial turmoil, respectively. This shows an increased attention of financial investors to commodity markets. Trends are also comparable when different stock indexes, such as the S&P 500, used by several authors (Creti et al., 2013; Silvennoinen and Thorp, 2013; Olson et al., 2014; Aboura and Chevallier, 2015) are considered. Consequently, movements in the correlations between commodity and traditional financial markets can be also driven by changes in the index composition and might justify some of the spillover effects observed in this chapter. This conjecture would be supported by Andriosopoulos and Nomikos (2014), who used energy-related stocks from the US and the UK markets to replicate the performance of physical-energy price returns. Yet, the lagged-squared-spread was found to be significant when volatility transmissions between NBP and FTSE100 were assessed, which supports fundamentals of supply and demand as drivers of the NBP spot price volatility.

3.8 Conclusions and Further Research

The present study contributed to the existing literature on price volatility dynamics in the natural gas markets by investigating the role played by fundamentals values of demand, supply and inventory, and cross-markets effects in driving price volatility in the UK natural gas spot market. More specifically, its key research questions were the following:

1. What are the implications of the theory of storage in the UK natural gas market? That is, what is the contribution of the fundamental values of demand, supply and inventory, in driving price volatility in the UK natural gas market?

2. To what extent does price volatility transmit whiting the UK natural gas and other energy markets?

3. Does price volatility transmit between natural gas and financial markets in the UK?

With respect to the first question, strong evidence of seasonality was found in the NBP spot-futures prices spread and thus in the convenience yield, which supported the theory of storage. There was evidence that changes in the spread enabled the identification and explanation of volatility dynamics in the NBP spot market, which were driven by seasonal fluctuations and unpredicted changes of the fundamental values of supply and demand. Although seasonal effects in the natural gas volatility are well known in the literature, their time-varying dynamics in the NBP natural gas spot prices have not been thoroughly investigated. Therefore, results in this chapter provide a contribution to the NBP derivatives valuation and are of interest to other European natural gas spot markets. Spot-futures spread dynamics and theory of storage implications were also found to provide an explanation for time-varying traded volumes in the NBP futures markets, thus entailing changes in the risk premium under different market conditions. Given the correlations between liquidity, price volatility and trading activity in the NBP market, which were documented in Chapter 2 of this dissertation, there are indications that predictions from the theory of storage also contribute to explain liquidity dynamics in the natural gas markets, which are valuable to regulators when monitoring market quality.

Cross-market effects were identified within energy markets, thus leading to the second research question raised in this chapter. Increasing integration between natural gas and power sectors was suggested in the UK natural gas, mostly supported by policy decisions, which would entail increased exposure of natural gas spot prices to the electricity generation mix. Greater exposure of natural gas prices to carbon prices may be also expected, following the introduction of the Carbon Price Floor uplift, which would reflect in higher NBP spot prices, with competitive disadvantages for the UK natural gas industry, relative other European nations, most of which have not introduced similar unilateral measures to price carbon. This might have implications for competitiveness and investment decisions in both the UK natural gas and power sectors. It may also affect the process of integration of European natural gas markets and overall its efficiency.

Time-varying dynamics were observed in the strength of the associations between NBP and Brent crude oil prices, as suggested by a reduction in the correlation between the two price series over time. This would entail changing risks for natural gas market players, who are reliant on traditional oil-linked pricing mechanisms. With hub prices eclipsing oil-indexation as reference price in the wholesale natural gas markets and anticipated increasing integration between natural and electricity markets, natural gas price convergence becomes crucial for sending right investment signals. This further motivates the investigation of the development of European hubs and drivers affecting wholesale natural gas markets integration, which will be addressed in Chapter 4 of this dissertation.

Although results showed cross-market effects between natural gas and financial markets, they did not permit to clarify the role of speculative trading and financial investors in spreading risk in the NBP market. Nonetheless, this chapter contributed to the debate by focusing on specific factors, namely the impact of fundamentals and market-capitalisation weights in the stock indexes composition, which may drive correlations and volatility spillovers and appear to have been neglected in previous research.

Appendix-Supplementary Analysis

A Co-movements within markets: An asymmetric DCC-GARCH approach

The dynamic conditional correlation (DCC) model (Engle, 2002) is among the simplest methods for examining co-movement of markets, mainly due to the smaller number of parameters when compared with the more parameterised BEKK. DCC GARCH models have the advantage of dropping the unrealistic hypothesis of time-invariance of the conditional correlations. Nonetheless, they do not allow for incorporating cross-market spillovers in the conditional variance-covariance matrix (Chang et al., 2013).

Similarly to the BEKK model in Eq (3.8)-(3.9), the conditional mean equation of the DCC specifications is assumed to be described by a vector autoregressive (VAR) model:

$$\begin{aligned} &\mathbf{r}_t = \Omega_0 + \Omega_1 \mathbf{r}_{t-1} + ... + \Omega_p \mathbf{r}_{t-p} + \boldsymbol{\epsilon}_t, \quad t = 1, ..., T, \\ &\boldsymbol{\epsilon}_t = H_t^{1/2} \boldsymbol{\eta}_t. \end{aligned} \tag{A.1}$$

Compared to the BEKK model, where the conditional variance-covariance matrix H_t is positive definite by construction, in the DCC model it is positive definite under conditions imposed on specific parameters and is defines as follows:

$$H_t = D_t R_t D_t, \tag{A.2}$$

where D_t is the 2×2 diagonal matrix of time-varying standard deviations from univariate GARCH models. In this appendix, the DCC structure introduced by Engle (2002) is adopted and asymmetric effects are considered, as in the BEKK specification in Eq (3.8)-(3.9). Therefore, the DCC is assumed in its asymmetric form, ADCC, as in Cappiello et al. (2006), which is as follows:

$$\begin{aligned} &Q_t = (1 - a^2 - b^2)\bar{R} - g^2 \bar{N} + a^2 \boldsymbol{\epsilon}_t \boldsymbol{\epsilon}_t' + b^2 Q_{t-1} + g^2 \boldsymbol{\epsilon}_{t-1}^- \boldsymbol{\epsilon}_{t-1}'^- \\ &R_t = diag(Q_t)^{-\frac{1}{2}} Q_t diag(Q_t)^{-\frac{1}{2}}. \end{aligned} \tag{A.3}$$

Q_t is a 2×2 matrix, which guarantees that R_t is a time-varying correlation matrix with ones on the diagonal and every other element ≥ 1 in absolute value; $\bar{R}$ is the unconditional correlation matrix and$\bar{N} = T^{-1} \sum_{t=1}^{T} \boldsymbol{\epsilon}_t^- \boldsymbol{\epsilon}_t'^-$.

The model in Eq. (A.1)-(A.3) is estimated through QMLE, according to the two-step procedure described in Engle (2002). In the first step, the univariate GARCH(p,q) model $h_t = \gamma + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-q} + \lambda s_{t-1,T}^2 + \delta x_{t-1,T}$ is estimated for each series in order to obtain the conditional variance-covariance matrix H_t. Estimation is carried out by controlling for the fundamental values, proxied by the lagged-squared-spread, $s_{t-1,T}^2$ and for the carbon emission price proxied by the EUA price, $x_{t-1,T}$. α_i, $i = 1, ..., p$ and β_j, $i = j, ..., q$ measure ARCH and GARCH effects, respectively.

In the second step, the return series are used to estimate the parameters of the matrix Q_t in Eq. (A-2) after standardisation through the standard deviations from the first step. Necessary and sufficient condition for R_t to be positive definite is $a^2 + b^2 + \psi g^2 < 1$, where $\psi =$ is the maximum eigenvalue of $\bar{R}^{-1/2} \bar{N} \bar{R}^{-1/2}$ (Cappiello et al., 2006; Silvennoinen and Teräsvirta, 2009). The GARCH order (p, q) is determined by SIC. Estimation is carried out through QML. The the log-likelihood function of the ADCC model in Eq. (A.1)-(A.3) is given by:

$$logL_t = -\frac{1}{2} \sum_{t=1}^{T} \left[2\ln(2\pi) + 2\ln|D_t| + \ln|R_t| + \boldsymbol{\epsilon}_t^{'} R_t^{-1} \boldsymbol{\epsilon}_t \right], \tag{A.4}$$

Parameter estimates and residual diagnostics of the bivariate VAR-ADCC models addressing co-movements between the NBP price series, and the Brent cruse oil, electricity and CIF ARA price series are presented in Table A.1. Overall, significant correlations are observed between the NBP and the other energy price series (coefficients a^2 and b^2 in rows nineteen and twenty-one of Table A.1), which support volatility spillovers in Table 3.9. Asymmetric effects are also found to be significant in the NBP-Electricity ADCC model (coefficient g^2 in row twenty of the table), which is in line with evidence from the BEKK specification.

Table A.1: Parameter estimates and residual diagnostics of the bivariate VAR-ADCC models of NBP and other energy markets

Model		NBP-Brent crude oil		NBP-Electricity		NBP-CIF ARA coal	
		NBP	Brent	NBP	Electricity	NBP	CIF ARA
Mean	ω_0	-0.076***	0.013	-0.095***	-0.043	-0.084**	0.008
		(0.028)	(0.029)	(0.032)	(0.028)	(0.034)	(0.014)
	$\omega_{1,1}$	0.102***	-0.033*	0.064***	0.089***	0.055**	0.120***
		(0.017)	(0.018)	(0.025)	(0.027)	(0.024)	(0.022)
	$\omega_{2,1}$	0.027*	-0.007	-0.010	0.022	-0.003	0.010
		(0.014)	(0.015)	(0.028)	(0.018)	(0.056)	(0.007)
Variance	γ	0.042***	0.012***	0.004***	0.039***	0.005	0.014***
		(0.009)	(0.005)	(0.010)	(0.008)	(0.010)	(0.003)
	α	0.095***	0.037***	0.081***	0.082***	0.085***	0.0656***
		(0.008)	(0.005)	(0.010)	(0.010)	(0.011)	(0.008)
	β	0.896***	0.960***	0.916***	0.899***	0.910***	0.898***
		(0.008)	(0.006)	(0.009)	(0.011)	(0.011)	(-0.013)
	λ	0.055**	0.038*	0.059***	0.067**	0.135**	-0.001
		(0.025)	(0.021)	(0.022)	(0.033)	(0.068)	(0.005)
	δ			0.003*	0.000	0.003*	0.000
				(0.001)	(0.001)	(0.001)	(-0.0003)
Correlation	a	0.003**	(0.001)	0.010***	(0.002)	0.003**	(0.002)
	g	0.000	(0.007)	0.008***	(0.003)	0.004	(0.004)
	b	0.990**	(0.020)	0.986***	(0.050)	0.990***	(0.040)
Residual Diagnostics	Skewness	0.188	-0.100	0.110	0.999	0.145	-0.013
	Kurtosis	3.907	3.437	3.266	4.270	3.350	5.302
	Ljung-Box (5)	9.500*	9.406	4.042	7.495	4.493	2.672
	ARCH test (5)	4.363	3.636	0.804	0.498	0.497	3.323**

Note: ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively.

Dynamic conditional correlations in Eq. (A.2) are shown in Figure A.1. The correlation between the NBP and Brent crude oil prices is on average 0.18 with standard deviation of 0.06 (Figure A.1 top plot). The correlation between NBP and Electricity price series, , which is shown in the middle plot of the figure, is found to be on average 0.74 (with standard deviation of 0.19). Finally, the correlation between the NBP and CIF ARA is on average 0.29 with standard deviation of 0.19 (bottom plot). Overall results support evidence from the BEKK in Eq. (3.8)-(3.9) and the time-varying features of co-movements of energy price series in the UK market.

Parameter estimates and residual diagnostics of the bivariate VAR-ADCC models addressing co-movements between the NBP and FTSE100 series are reported in Table A.2. Significant correlations are found between the two price series, which are inferred by the

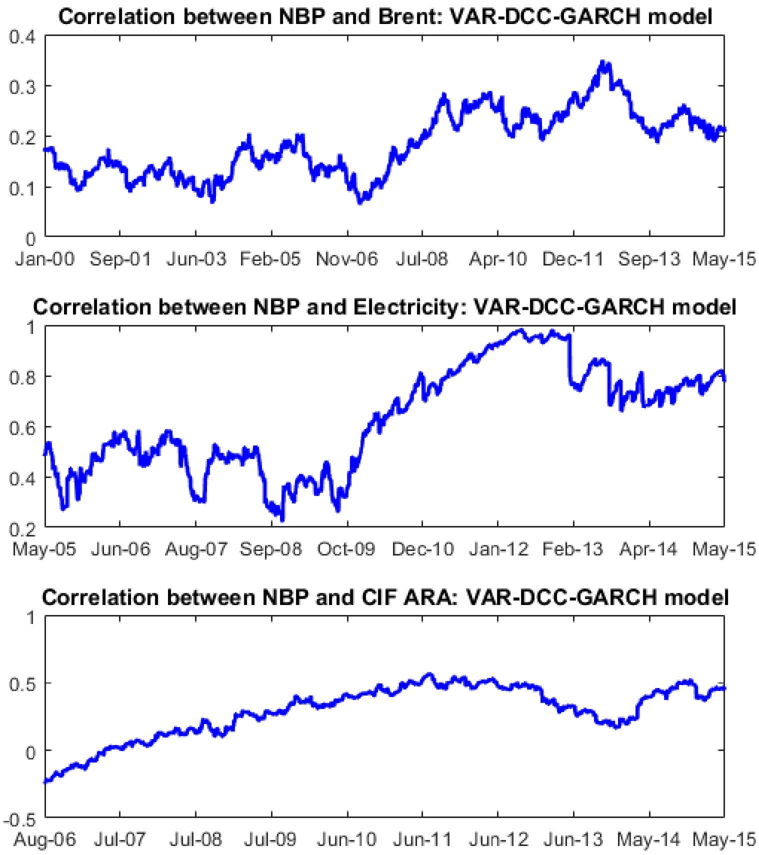


Figure A.1: Conditional correlations between the NBP and other energy markets of the VAR-ADCC models

coefficient b^2 in row twenty-one, which support results from the BEKK model in Table 3.10.

The dynamic condition correlation between NBP and FTSE100 is shown in Figure A.2 and is found to be on average 0.0031 with standard deviation of 0.0007. Therefore, lower variability is observed in the link between natural gas and financial markets via ADCC compared to the BEKK. Nonetheless, the ADCC model supports the time-varying feature of this link, which is mainly evident during the 2007-08 financial crisis and in its aftermath, thus in line with the BEKK parameter estimates.

Table A.2: Parameter estimates and residual diagnostics of the bivariate VAR-ADCC model of NBP and FTSE100

		NBP-FTSE100	
Mean	ω_0	-0.076***	0.013
		(0.028)	(0.014)
	$\omega_{1,1}$	0.105***	-0.031*
		(0.018)	(0.019)
	$\omega_{2,1}$	-0.007	-0.013*
		(0.028)	(0.007)
Variance	γ	0.041***	0.0104***
		(0.009)	(0.003)
	α	0.095***	0.067***
		0.008	(0.007)
	β	0.897***	0.922***
		0.008	(0.008)
	λ	0.056**	-0.008*
		0.024	(0.005)
Correlation	a	0.000	(0.008)
	g	0.000	(0.006)
	b	0.832***	(0.428)
Residuals Diagnostics	Skewness	0.182	-0.260
	Kurtosis	3.885	3.320
	Ljung-Box (5)	10.21*	4.947
	ARCH test (5)	1.0277	19.09**

Note: ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively.

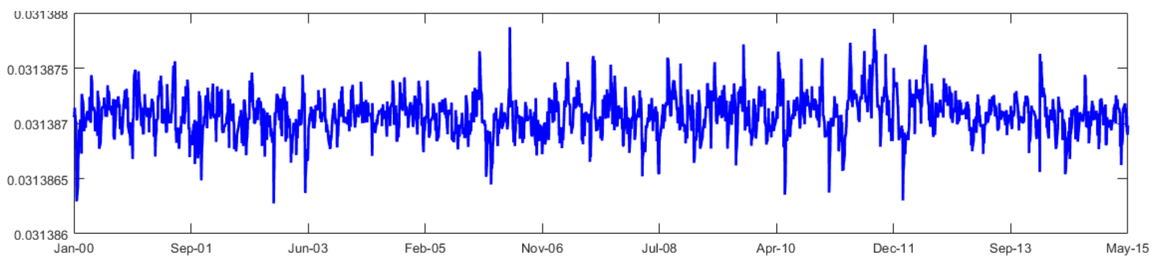


Figure A.2: Conditional correlations between the NBP and FTSE100 from the VAR-ADCC model

4

European Natural Gas Markets Integration and the Relationship between Natural Gas and Crude Oil Markets

4.1 Introduction

The preamble to a single European natural gas market envisaged by the Third Energy Package (European Commission, 2009) is the integration of natural gas systems, such that price differences across hubs should only reflect transmission fees. It follows from the concept of perfect market integration by Cournot (1897) and entails that prices at different trading hubs should follow overall changes in the fundamental values in the same way and simultaneously, thus implying zero arbitrage opportunities. Consequently, hub price signals and price convergence are crucial to guarantee competitive natural gas despatching and economically sensible investment decisions, as stated in the Gas Target Model, which was described in Chapter 1.

Studies thus far provide some evidence of increasing price convergence at European natural gas hubs (Siliverstovs et al., 2005; Neumann et al., 2006; Neumann and Cullmann, 2012; Heather, 2015; Miriello and Polo, 2015; Petrovich, 2015; Kuper and Mulder, 2016; Petrovich, 2016). This evidence was mostly based on a common underlying pricing mechanism, reasonably driven by oil-indexation (Asche et al., 2013). However, differently evolving natural gas pricing mechanisms and oil-linking, as described in Chapter 1, may affect natural gas prices at European hubs and have implications for their convergence and market integration, which appear to have been neglected in previous research.

In this chapter, the process towards price convergence in European wholesale natural gas markets is analysed and the relationship between natural gas and crude oil prices is investigated. The main goal of the analysis is to assess the degree of integration between European natural gas markets and identify factors that may foster or prevent this integration. A robust multivariate long-run dynamic approach is used, which allows for outliers, seasonalities, leptokurtosis and GARCH effects in the energy price series, and is thus expected to provide more reliable results than previous studies, where standard cointegration analysis is used. Findings in this chapter have implications for market players, concerned about managing new risks brought by evolving markets, and for policy-makers, who value the overall efficiency of European energy markets.

The remainder of this chapter is organised as follows. In Section 4.2, the literature in the field is outlined. Section 4.3 states the research questions. Section 4.4 presents the methodologies. Data are described in Section 4.5. Results are reported in Section 4.6 and discussed in Section 4.7. Section 4.8 concludes and assesses the study's implications for the literature and future research.

4.2 Literature Review

Following the liberalisation process, some authors have investigated price convergence in European natural gas markets. Asche et al. (2001, 2002) assessed the convergence of the monthly oil-linked long-term contract prices of Belgium, France and Germany in the period 1990-97. Despite significant price differentials, the authors argued that prices moved proportionally through the period, mostly due to oil-indexation, thus entailing high integration. Similar evidence was reported by Siliverstovs et al. (2005) concerning Continental Europe gas markets between the early 1990s and 2004.

Price convergence in day-ahead markets was investigated by Neumann et al. (2006), at the trading hubs NBP, Zeebrugge and Bunde[1]. Day-ahead prices in the period 2000-05 suggested high convergence between the NBP and Zeebrugge prices, which was attributed to *Interconnector*, the pipeline that links the UK and Belgium markets. By contrast, the authors failed to find convergence between the Zeebrugge and Bunde prices, despite the two locations being physically connected. This lack of convergence was attributed to the low liquidity at the Bunde hub and inefficiencies in transmission capacity allocation. Neumann and Cullmann (2012) investigated the convergence of day-ahead prices at Continental Europe hubs in the period 2009-11. Low convergence was found, which the authors ascribed to the high number of trading hubs with different trading procedures, which prevented interconnections to be efficiently managed.

While investigating integration within the Dutch and German markets, Growitsch et al. (2015) found convergence between daily day-ahead prices at their hubs during the period 2007-11. Their conclusion was also supported by Kuper and Mulder (2016) in the period 2007-13. Nonetheless, they also observed that integration reduced after the expansion in the interconnection between the UK and Netherlands markets and the increase in Germany imports from Russia through oil-linked long-term contracts.

Miriello and Polo (2015) observed differences in trading activity at the German and Italian hubs relative to the British and Dutch hubs during the period 2008-13. The authors noticed a smaller fraction of the overall traded gas flowing through the NCG, GasPool and PSV hubs in comparison with the NBP and TTF hubs. They argued that German and Italian hubs were mostly reselling volumes from long-term contracts, which implied a predominance of long-term contracts for gas procurement relative to hub trading in Germany and Italy.

Petrovich (2015) found differences in the day-ahead price correlations across hubs, with North-West European hubs (NBP, TTF, Zeebrugge, PEG North, and German hubs) show-

[1] Bunde is a physical entry point into Germany which lies near the border with the Netherlands and is about 50 kilometres east of Groningen. A full price history at Bunde can be obtained from ICIS Heren. Liquidity at the trading point has deteriorated significantly since the development of the Dutch virtual TTF hub. At present, the ICIS Bunde price assessment covers the identical range of contracts quoted at TTF (Source: ICIS Heren, Continental Gas Snapshot Methodology, August 2013)

ing greater integration than the Italy (PSV), Austria (CEGH) and Southern France (PEG South) hubs. The author also highlighted unexploited arbitrage opportunities between markets, which implied the absence of price convergence at European hubs. In a similar vein, Heather (2015) observed varying correlation across month- and day-ahead European natural gas prices, as well as different levels of liquidity and trading activity at their hubs. By contrast, Renou-Maissant (2012) focused on biannual industrial prices to assess integration within the Belgian, French, German, Italian, Spanish and British markets in the period 1991-2009. Results showed an on-going and heterogenous process of convergence within Continental markets, and between them and the UK market. This heterogeneity was explained as a consequence of distortions in the liberalisation process, which may have favoured dominant positions.

As a whole, despite some indications of greater convergence, the empirical evidence of market integration thus far is mixed. Location and interconnection may play a role, since convergence appears to be greater in North-West European markets than in the Central-Southern. Nonetheless, market integration might have reflected oil-linked long-term contracts, which entail a common pricing mechanism that resulted in price convergence (Asche et al., 2001, 2002; Siliverstovs et al., 2005; Renou-Maissant, 2012). This interpretation, however, would be in contradiction with differences between price dynamics in North-West Europe, where gas-on-gas competition is greater, and Central-South Europe, where gas-on-gas penetration is lower, as shown in Chapter 1. This view is also questioned by evidence from Miriello and Polo (2015) and Kuper and Mulder (2016), who observed decreased integration between Dutch and German markets, following greater volumes of gas imported subject to oil-indexation in Germany. Consequently, it can be argued that oil-indexation may either foster or prevent hub trading and development, thus affecting liquidity and price harmonisation within European markets, and this appears to have not been thoroughly investigated in previous literature.

Most of the literature on market integration (e.g. Asche et al., 2001, 2002; Siliverstovs et al., 2005; Neumann et al., 2006; Renou-Maissant, 2012; Growitsch et al., 2015; Kuper and Mulder, 2016) relied on standard unit root tests, and cointegration procedures (Dickey and Fuller, 1979, 1981; Engle and Granger, 1987; Johansen, 1988, 1991) to investigate time series properties and assess price convergence. However, standard cointegration analysis has been showed to be biased towards the rejection of the unit root hypothesis in the presence of outliers and fat tailed distributions (e.g. Franses and Haldrup, 1994; Arranz and Escribano, 2004), which are main features of energy price series, as was also observed in Chapters 3. Given the relevance of both the natural gas-oil price relationship in Europe and the methodological approach in assessing drivers of price convergence, the related streams of literature are reviewed below.

4.2.1 The relationship between crude oil and natural gas prices

By exploring the relationship between natural gas and crude oil prices in the UK during the period 1995-99, Asche et al. (2006) observed high convergence between the two price time series, which they argued had been affected by the increased physical interconnection with Continental Europe. Panagiotidis and Rutledge (2007) investigated the relationship between UK wholesale natural gas and Brent crude oil prices from 1996 to 2003, in order to ascertain de-links that may have followed the natural gas market liberalisation. The authors identified cointegrating relationships between the two price time series and argued that these had been fostered by greater physical interconnection with Continental Europe and thus was due to oil-linked long-term contracts.

By using monthly prices, Asche et al. (2013) observed a positive correlation between spot and oil-linked contract gas prices in North-West Europe over the period 1999-2010, and concluded that oil prices drove both contract and spot prices in Europe in the period. This entailed high integration between the two markets, regardless of the pricing mechanisms underlying natural gas trading. Furthermore, by analysing the one-month-ahead NBP weekly prices in the period 1997-2014, Asche et al. (2015) observed that natural gas prices tended to follow a pricing process that was independent of oil prices during the winter. The correlation between the two price series was however observed to be stronger from 2011 onwards, when oil prices were stable and low seasonality was found to affect the natural gas prices. Therefore, the strength of the link between natural gas and crude oil prices was ascribed to seasonalities in the natural gas demand. A similar conclusion was offered by Hartley and Medlock (2014), who stressed the role of technological breakthroughs in the power sector in explaining changes in the correlation between natural gas and crude oil prices. Further assessments of the correlation between natural gas and crude oil prices in European markets include Bachmeier and Griffin (2006), Villar and Joutz (2006), Brown and Yücel (2009), Ramberg and Parsons (2012) and Brigida (2014), which also highlighted the time-varying nature of the relationship between the two prices. Yet, the liberalisation of European natural gas markets has led a debate on whether it brought an independent pricing process for natural gas, which reflects the competitive interplay of supply and demand (Asche et al., 2006; Panagiotidis and Rutledge, 2007; Asche et al., 2013).

With hub prices replacing oil-indexation as reference price in the wholesale natural gas markets and Europe's dependency on a restricted number of suppliers (Russia, Norway, Algeria and Qatar) with oil-linked long-term contracts, it is crucial for the security of supply and efficiency to assess the alignment of hub prices. In addition, it is important to gain insights into the role played by oil-indexation in driving or preventing this alignment. A thorough analysis requires reliable procedures, which account for the peculiar features of the energy price time series. The methodological literature is therefore reviewed in the next sub-section.

4.2.2 Testing energy price convergence and market integration

Econometric literature has showed that standard unit root tests are biased towards the rejection of the unit-root hypothesis, when outliers and fat tails affect the time series distributions (Franses and Haldrup, 1994; Hoek et al., 1995; Lucas, 1995a,b; Franses and Lucas, 1998; Arranz and Escribano, 2004), or in the presence of fractional integration (Diebold and Rudebusch, 1991; DeJong et al., 1992; Hasslers and Wolters, 1994; Lee and Schmidt, 1996). This bias, which appears to have been neglected in empirical studies of natural gas market integration, has however received some attention in studies on electricity markets. Following Boswijk (2000) and Arranz et al. (2002), Escribano et al. (2011) proposed a procedure allowing for GARCH effects and outliers when testing for unit roots in electricity price time series. The authors adopted likelihood-ratio type statistics to cope with the power loss of the traditional least-squared Dickey-Fuller tests in presence of GARCH effects (Boswijk, 2000). They also applied a median filter (Arranz et al., 2002) to the original daily price series in order to improve the performance of the tests in presence of outliers and seasonalities. Based on this research, Bosco et al. (2010) investigated price convergence in European electricity markets by adopting cointegration procedures based on pseudo-likelihood-ratio type statistics (Lucas, 1995a,b) and multivariate KPSS statistics (Nyblom and Harvey, 2000), which also allow for GARCH effects, outliers and seasonalities.

The application of cointegration analysis to investigate price convergence relies on the assumption of a stable long-run relationship, which is implicit in the definition of perfect market integration as entailed by the law of one price (LOP) (Cournot, 1897; Stigler and Sherwin, 1985). Discrepancies in the price series for a same product should be described by a stationary and mean-reverting process, as argued, for instance, by Froot and Rogoff (1995) or Sarno and Taylor (2002) in studies of purchasing power parity and real exchange rate. A similar approach was also used by Pesaran (2007) to assess output and economic growth convergence among European countries.

Cointegration entails that price convergence has to be completed during the time period considered, so that market integration can be detected. Since convergence refers to a process, when it is on-going, the hypothesis of stationarity underlying the cointegration assumption would be rejected. Consequently, in order to allow for dynamics in the convergence process, different approaches have been used in econometric literature. Rolling cointegration tests based on the Johansen's procedure (Hansen and Johansen, 1999; Johansen et al., 2000) have been adopted for instance by de Menezes and Houllier (2016) to assess the integration European electricity markets. State-space models (Harvey, 1990) have been also proposed in literature, which rely on the degree of convergence and are independent of non-stationarity. Moreover, state-space models permit to relax the normality assumption of the innovation process, thus making the parameter estimates reliable, in the sense of minimum mean squared error, when the variables do not follow a Gaussian distribution (Durbin and Koopman, 2001).

Overall, energy price time series have been found to be stationary and mean-reverting (de Jong and Huisman, 2002; Escribano et al., 2011; Lucia and Schwartz, 2002; Huisman and Mahieu, 2003; Lee et al., 2006; Elder and Serletis, 2008; Lee and Lee, 2009) but also non-stationary and persistent (Koopman et al., 2007; Maslyuk and Smyth, 2008; Bosco et al., 2010; Ghoshray and Johnson, 2010; Ozdemir et al., 2013; Barros et al., 2014; Presno et al., 2014). Mixed evidence was also found in electricity markets (de Menezes et al., 2016) and in natural gas markets it can be inferred by the results in Chapter 3. Nonetheless, it is noteworthy that a significant share of this research focused on the period 1990s-early 2000s, which was characterised by low price volatility in energy markets and more stable and stationary price time series. In all, the impact of outliers, seasonalities, leptokurtosis and GARCH effects in the energy price series has been neglected by most researchers when assessing cointegration.

4.3 Research Questions

The different bodies of literature reviewed in the previous section highlight two distinct aspects of convergence, namely: the convergence as a state of the market, as implied by the LOP; and the convergence as a process, as assumed by state-space models. Distinct pathways can be entailed in the integration of European natural gas markets. These pathways can be identified in the forward markets. As argued by Bunn and Gianfreda (2010), by reflecting expectations and being less exposed to shorter-term market conditions, the forward markets would better reveal price convergence relative to day-ahead markets, which mostly reflect local demand and supply shocks. Nonetheless, day-ahead markets better suit arbitrage and trading opportunities within markets, which may foster price convergence.

Questions emerge concerning the role of oil-linked long-term contracts in the process towards the European natural gas market integration. In this chapter, the following research questions are addressed:

1. Are European natural gas markets moving towards a single market? Are there differences in price convergence between forward and day-ahead markets?

2. How is the link between natural gas and crude oil prices evolving in European markets? What are the implications for the integration process?

Since natural gas forward prices are expected to be more affected by oil-indexation relative to day-ahead prices, assessing price convergence in both markets is key to ascertain the progress towards a single market. This analysis is of interest for researchers in energy markets, but also for market players, interested in managing their risks, and for policymakers, who are concerned about the performance of the European energy system. In the next section, the methodological approach used to address the stated research questions is described.

4.4 Methodology

4.4.1 Investigating price convergence in the natural gas markets

In this chapter, a pairwise state-space approach is used to investigate price convergence European hubs. This framework allows for time-varying dynamics across markets. Based on Pesaran (2007), convergence is assumed between two hub prices if their difference is a process with constant mean. This condition can be described as follows:

$$p_{i,t} - p_{j,t} = m_t + \epsilon_t, \quad t = 1, ..., T, \tag{4.1}$$

$$m_t = m_{t-1} + \eta_t, \quad \eta_t \sim N(0, \sigma_\eta^2), \tag{4.2}$$

where $p_{i,t}$ is the logarithm of the price in the market i at time t, $p_{j,t}$ is the logarithm of the price in the market j, m_t is the state variable and ϵ_t is a white noise innovation process, such that is $\epsilon_t \sim N(0, \sigma_\epsilon^2)$. Eq. (4.1) represents the measurement equation, which has the structure of a linear regression model with time-varying coefficients; Eq. (4.2) is the transition equation that describes the evolution of the state variable over time with error terms restricted to be normally distributed. The state variable represents factors with a direct interpretation, which in this chapter are differences in the response to changes in the supply and demand fundamentals. These differences are expected to be reflected on the transmission system functioning and indicate discrepancies in transmission fees, capacity constraints, temporary capacity contractual congestion, as highlighted by ACER (2015b). Such factors cannot be directly observed and may affect market integration. Therefore, the closer m_t to zero, the higher is the convergence between the two prices.

The transition equation represents a random walk with noise. Hence, the state-space model is non-stationary in the sense that the distribution of the random variables $p_{i,t} - p_{j,t}$ and m_t changes over time. Due to the Markovian nature of state-space models, estimation can be carried out in a recursive way through a Kalman filter (Harvey, 1990), based on information available at time $t-1$. The parameters obtained by Kalman filtering track price convergence through graphical examination of the time-varying coefficients m_t: the closer m_t to zero, the greater the price convergence, the higher is the integration between markets. The hypothesis of market integration is then tested via robust procedures, as described below.

4.4.2 Assessing integration of natural gas markets, and between natural gas and crude oil markets

The approach by Franses and Haldrup (1994), Lucas (1997) and Franses and Lucas (1998) is here adopted to investigate integration in European natural gas markets, and between natural gas and oil markets. This approach has been used by Escribano et al. (2011) and Bosco et al. (2010) when investigating integration in European electricity markets.

A vector autoregressive model of order $q+1$, VAR$(q+1)$, is thus considered in its error correction representation VECM, which is defined as:

$$\Delta \mathbf{p}_t = \alpha\beta' \mathbf{p}_{t-1} + \Phi_1 \Delta \mathbf{p}_{t-1} + ... + \Phi_q \Delta \mathbf{p}_{t-q} + \Psi D_t + \varepsilon_t, \quad t = 1, ..., T \tag{4.3}$$

where $\mathbf{p}_t$ and ε_t are $(k \times 1)$ column vectors, $\Phi_1, ..., \Phi_q$ are $(k \times k)$ parameter matrices, D_t is a matrix of deterministic regressors (constant and a linear trend), Ψ is a matrix of parameters and $\Pi = \alpha\beta'$ is the $(k \times r)$ parameter matrix of full column rank, where is $0 < r < k$. If ε_t is assumed to be a white noise process with zero mean, its positive definite covariance matrix Σ and the model in Eq.(4.3) can be estimated, with and without reduced rank restrictions on Π, by likelihood ratio (LR) statistics (i.e. Johansen's trace test) for the null hypothesis $H_0 : rank(\Pi) \leq r$ against the alternative $H_a : rank(\Pi) = k$ (Johansen, 1988, 1991). Thus, under suitable conditions on the parameter matrices, r linear combinations $\beta' \mathbf{p}_{t-1}$ can be shown to be stationary and identify cointegrating relationships among the price series, which are represented by the columns of β.

A testing procedure based on a Student-t likelihood ratio (PLR) is adopted, which has been proved to be robust to outliers and fat-tailed distributions (Lucas, 1997; Franses and Lucas, 1998). Furthermore, to overcome the detrimental effects of misspecified likelihood functions on the consistency of parameter estimates and their inference, an expectation-maximisation (EM) algorithm is used. This algorithm is based on iteratively re-weighted least squares and is an efficient method for maximum likelihood estimation with latent variables (Dempster et al., 1977, 1980). Finally, a bootstrap is adopted to approximate the asymptotic distribution of the PLR statistics involving latent variables (Swensen, 2006). This stepwise procedure can be summarised as follows:

Step 1. PLR statistics are constructed for the null hypothesis $H_0 : rank(\Pi) \leq r$ against the alternative $H_a : rank(\Pi) = k$, in Eq. (4.3):

$$PLR \quad = \quad 2T \left(\mathcal{L}(\hat{\theta}) - \mathcal{L}(\tilde{\theta}) \right) \tag{4.4}$$

where $\tilde{\theta}$ and $\hat{\theta}$ denote the parameter vectors under the null and alternative hypotheses, respectively, and are estimated using Student-t with ν degree of freedom. The pseudo-log-likelihood function is defined as follows:

$$\mathcal{L}(\theta) = \quad log\left[\frac{\Gamma\left(\frac{\nu+k}{2}\right)}{\Gamma\left(\frac{\nu}{2}\right)\sqrt{(\pi\nu)^k}}\right] - \frac{1}{2}log|\sum| - \frac{\nu+k}{2}\sum_{t=1}^{T} log\left(1+\frac{\varepsilon_t'\sum^{-1}\varepsilon_t}{\nu}\right). \tag{4.5}$$

For $\nu \to \infty$, the distribution collapses to a multivariate Normal distribution. Hence, an estimate of ν, also called "tail index", is obtained by using the technique by Hill (1975), which is as follows:

$$\hat{\nu} = \left[\frac{1}{h}\sum_{i=1}^{h} log\frac{\hat{\upsilon}_{T-h+i}}{\hat{\upsilon}_{T-h}}\right]^{-1} \tag{4.6}$$

where $\hat{\upsilon}_{(s)}$ is the $s-th$ order statistic (in descending order) of the absolute values of the residuals from fitting an AR model of order q on the price series p_t in Eq. (4.3) to attenuate the impact of serial dependence in the data, with q being identified using SIC. The threshold h is set equal to $\left[T^{3/4}/logT\right]$. This approach follows Trapani (2016), who also reviewed the Hill's estimator and proposed improvements to moment testing. Thus, the model in Eq. (4.3) is estimated and the results are used to initialise the EM iterations as described below.

Step 2. The multivariate Student-t PLR estimator can be regarded as the Gaussian PLR estimator for a weighted version of the model in Eq. (4.3) with weights given by:

$$\hat{w}_t = \left(\frac{\hat{\nu}+k}{\hat{\nu}+\varepsilon_t'\sum^{-1}\varepsilon_t}\right)^{\frac{1}{2}}, \tag{4.7}$$

such that observations with unusually large values of ε_t receive a smaller weight. These weights are available for inspection after the procedure is implemented and the test statistics computed, because abnormal observations signal the underlying error-correction mechanism. Under the assumption that ε_t are standard normally distributed, that is no outliers or fat tails are observed, w_t^2, which is bounded from above by $(\hat{\nu}+k)/\hat{\nu}$, has a χ^2 distribution with k degree of freedom. Let $c_k(0.01)$ denote the 1% critical value of a χ^2 distribution with k degree of freedom; weights are observed to be particularly small if $w_t \leq (\hat{\nu}+k)/(\hat{\nu}+c_k(0.01)$ and indicate that the error-correction mechanism at that time should be inspected.

The EM algorithm is thus implemented recursively, as follows:

EM1. Using the parameters from Step 1, the weights are computed as in Eq. (4.7).

EM2. The weights are thus used to estimate the model in Eq. (4.3) after having multiplied the variables on both sides of the equal sign by $\hat{w}_t$. If the pseudo-likelihood increment with respect to the last iteration is greater than a predetermined tolerance (0.0001), the EM algorithm returns to $EM1$, otherwise it stops the iteration. Similar to Franses and Lucas (1998) and with the aim to reduce the bias induced by a misspecified null hypothesis, in this chapter weights are evaluated using parameter estimates under the alternative hypothesis $H_a : rank(\Pi) = k$. A maximum of 500 iterations is specified.

Step 3. Finally, the bootstrap uses independent resampling and is implemented as follows:

(i) The model in Eq. (4.3) is estimated under the alternative hypothesis $H_a : rank(\Pi) = k$ and Student-t innovations using the EM algorithm, as described above. Its residuals $\varepsilon_{q+2}, ..., \varepsilon_T$ are thus computed.

(ii) The model in Eq. (4.3) is estimated under the null hypothesis $H_0 : rank(\Pi) \leq r$, $r = 0, 1$ and Student-t innovations using the EM algorithm.

(iii) Bootstrap samples are generated using $\mathbf{p}_1, ..., \mathbf{p}_{q+1}$ as initial values; the parameters estimated under the null hypothesis in (ii) and the resampled residuals $\hat{\varepsilon}_{p+2}, ..., \hat{\varepsilon}_T$ in (i).

(iv) The PLR statistics for the null hypothesis $H_0 : rank(\Pi) \leq r$ against the alternative $H_a : rank(\Pi) = k$ is computed at each bootstrap sample in (iii).

The bootstrap strategy in (i)-(iii) uses 10,000 replications and the $p - value$ is the relative frequency of bootstrapped PLR statistics which are greater than the PLR statistics computed from the original sample in Step 1.

The methodological approach in Step 1 - Step 3 is also applied in its univariate fashion through Augmented Dickey-Fuller (ADF) tests to investigate trends in the series. As PLR statistics are based on ADF and Johansen's tests, the cases of intercept and trend and intercept are considered (Bosco et al., 2010). The analysis is performed at different orders of lags q in Eq. (4.3); q is selected according to SIC to minimise serial dependency in the residuals. In the next section, the data used in the empirical study are described and their preliminary analysis is presented.

4.5 Data

4.5.1 Dataset

The data set consists of daily (Monday-Friday) one-month-ahead and day-ahead forward prices, as recorded in the OTC markets at the following hubs: NBP (United Kingdom), TTF (the Netherlands), Zeebrugge (Belgium), NCG and GasPool (Germany), PEG North (France), AVTP (Austria) and PSV (Italy). OTC contracts have been considered as they represent 70% of the total traded volume at European hubs, as shown in Figure 1.1 of Chapter 1. One-month-ahead and day-ahead maturities have been used, which were also investigated in previous research (Neumann et al., 2006; Bosco et al., 2010; Neumann and Cullmann, 2012; Asche et al., 2015; Miriello and Polo, 2015).

One-month-ahead forward prices were available from Thomson Reuters-Eikon. Day-ahead prices were collected from Thomson Reuters-Eikon for the hubs NBP, TTF, Zeebrugge, NCG, PSV; day-ahead PEG North prices were available from Powernext. The data were accessible in their original currency and unit, i.e. GBpence/therm for NBP and Zeebrugge, Euro/MWh otherwise. Therefore, prices have been converted to Euro/MWh by using exchange rates at the corresponding maturities, as available from Thomson Reuters-Eikon (one-month-ahead series) and Bank of England (day-ahead). The factor used to convert prices from therm to MWh was 0.0293071 (Platts, 2016).

One-month-ahead forward contracts have been considered for Brent crude oil. Prices were accessible from Thomson Reuters - Eikon and recorded in US dollar/barrel. A lag of six months is assumed in the crude oil price series, as it is common industry practice to include lagged six-month average oil prices in the oil-linked natural gas pricing of the long-term contracts (Platts, 2016).

On the whole, the data set covers the period 2 January 2008 - 29 January 2016 but the time series were available over different periods, with a common last observation recorded on 29 January 2016. At each stage of the empirical analysis, the longest available period and the longest overlapping period have been considered.

A median filter was applied to the daily series, which preserves the trends in the natural gas prices while smoothing outliers, seasonalities and volatility clustering (Escribano et al., 2011; Arranz and Escribano, 2004; Bosco et al., 2010). Therefore, weekly (Monday-Friday) median prices have been used in the empirical study. Preliminary analysis of the series after median filtering is presented below.

4.5.2 Preliminary analysis

Descriptive statistics of the weekly medians of the daily one-month-ahead forward prices at European hubs (in Euro/MWh), and their returns are presented in Panel (a) and Panel (b) of Table 4.1, respectively. The first four moments (Mean, Std.Dev., Skewness and Kurtosis) are shown in rows two to five. Median, minimum and maximum values are given in rows six to eight. Rows nine, ten and eleven report the p-values of the Jarque-Bera statistics for the assumption of normal distribution, Ljung-Box statistics for the null hypothesis of serial independence and ARCH tests for the null hypothesis of homoscedasticity. These statistics were computed at the 20^{th} order of lags, spanning five months and thus accounting for seasonal effects in the price series, as observed in Chapter 2 and Chapter 3 of this dissertation. Rows twelve and thirteen of Panel (a) indicate the first observation of each series and the total number of observations, respectively.

Higher prices are observed at the Italian PSV hub compared to other European hubs (Panel (a) of Table 4.1), as implied by pairwise t-tests and non-parametric sign tests for equal means and medians. Overall, the hypothesis of normality is rejected at 1% significance level (10% when the PSV is considered), as well as the hypotheses of homoscedasticity and serial independence. Pairwise t-tests, non-parametric sign tests and F-tests indicate similar distributions of the one-month-ahead NBP, TTF and Zeebrugge price series.

Higher volatility is observed at the NBP, TTF, Zeebrugge and NCG hubs than at other hubs, which is suggested by pairwise F-tests on the price returns (Panel (b) of Table

4.1). Price returns have skewed and leptokurtic distributions, which reject normality, as indicated by their Jarque-Bera tests. Significant ARCH effects are also observed in these series. With the exception of Zeebrugge, Ljung-Box statistics fail to reject serial independence. Together these statistics highlight the prevalence of fat tails and volatility clustering in the natural gas price and return distributions, even after median filtering.

Table 4.1: Descriptive statistics of the weekly medians of the daily one-month-ahead forward prices at European hubs (in Euro/MWh) and their returns

	NBP	TTF	Zeebrugge	NCG	GasPool	PEG North	AVTP	PSV
Panel (a): Prices								
Mean	21.36	21.41	21.36	21.28	22.98	20.98	23.88	25.84
St.Dev.	5.570	5.402	5.523	5.362	3.349	5.378	3.385	4.132
Skewness	-0.441	-0.553	-0.510	-0.513	-0.433	-0.689	-0.731	-0.296
Kurtosis	2.78	2.72	2.73	2.67	2.492	2.45	2.581	2.623
Median	22.43	22.53	22.50	22.43	23.25	22.25	24.60	26.85
Min	7.69	8.07	7.75	8.03	13.27	8.10	13.88	15.00
Max	38.82	35.00	36.67	35.38	28.75	29.13	28.55	34.25
Jarque-Bera	0.004***	0.001***	0.002***	0.002***	0.009***	0.001***	0.001***	0.069*
ARCH (20)	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Ljung-Box (20)	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
1st Obs	2/01/08	2/01/08	02/01/08	26/08/08	1/09/10	9/03/09	7/07/11	7/07/11
Obs.	426	426	426	392	285	363	241	241
Panel (b): Returns								
Mean	-0.0014	-0.0015	-0.0015	-0.0018	-0.0012	0.0002	-0.0022	-0.0023
St.Dev.	0.052	0.046	0.051	0.047	0.034	0.045	0.033	0.029
Skewness	0.645	0.116	-0.396	0.323	2.137	0.798	1.473	1.054
Kurtosis	10.77	7.506	10.72	8.592	18.08	9.081	19.42	8.745
Median	-0.0039	-0.0042	-0.0027	-0.0043	0.0000	0.0000	0.0000	-0.0013
Min	-0.2840	-0.2194	-0.3436	-0.2367	-0.1295	-0.2057	-0.1897	-0.0853
Max	0.3121	0.2039	0.2268	0.2250	0.2649	0.2276	0.2236	0.1705
Jarque-Bera	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
ARCH (20)	0.000***	0.001***	0.001***	0.002***	0.900	0.004***	0.000***	0.213
Ljung-Box (20)	0.165	0.247	0.007***	0.235	0.838	0.173	0.216	0.155
Obs.	425	425	425	391	284	362	240	240

Weekly medians of the daily one-month-ahead forward prices at European hubs (in Euro/MWh) and their returns are shown in Figures 4.1 and 4.2, respectively. During overlapping periods, similar pathways are observed in the series, which are mainly noticeable from 2012 onwards and indicate some co-movements of European natural gas forward markets (Figure 4.1). Similar pathways are also observed in the price return series, in particular when market price volatility is high, as in 2014 and in the first half of 2015

(Figure 4.2).

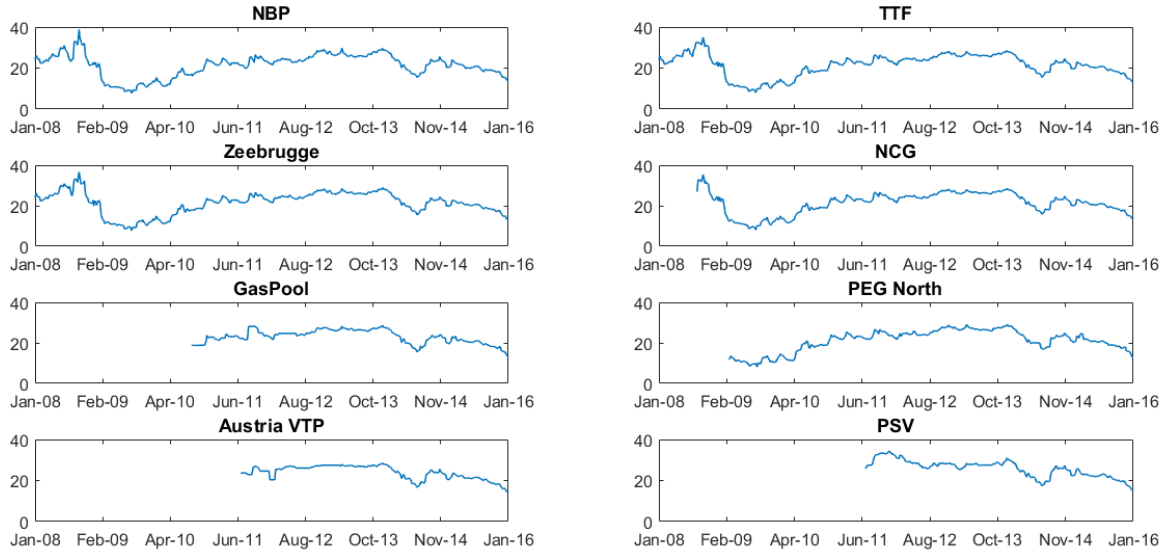


Figure 4.1: Weekly medians of the daily one-month-ahead forward prices at European hubs (in Euro/MWh)

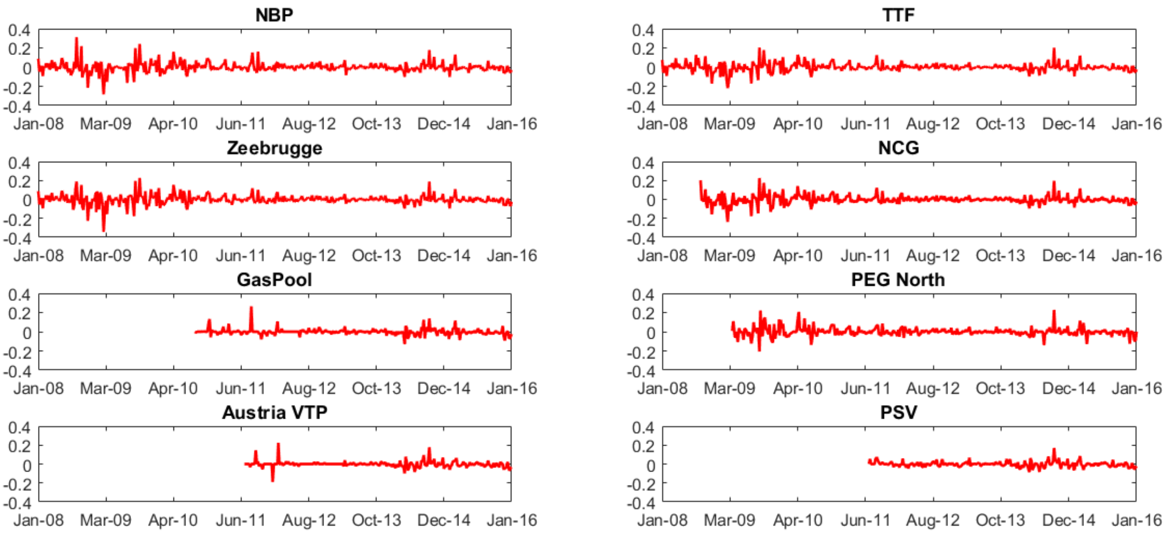


Figure 4.2: Returns of the weekly medians of the daily one-month-ahead forward prices at European hubs

Panels (a) and (b) of Table 4.2 present the descriptive statistics of the weekly medians of the daily day-ahead prices at European hubs (Euro/MWh) and their returns, respectively. Mean, standard deviation, skewness and kurtosis are reported in rows two to five. Rows six to eight show median, minimum and maximum values. In rows nine-eleven, the p-values of the Jarque-Bera, Ljung-Box and ARCH tests are presented, which were computed at the 20^{th} order of lags. Rows twelve and thirteen of Panel (a) show the first observation of each series and the total number of observations.

Higher prices are observed at the Italian PSV hub, which are confirmed by pairwise t-tests and non-parametric sign tests. This is in line with observations in the one-month-ahead forward market (Table 4.1 Panel (a)). NBP, TTF, Zeebrugge and PEG North are more volatile, as inferred by pairwise F-tests. Asymmetries and ARCH effects are observed in the day-ahead price distributions, even after filtering. Not surprisingly, Jarque-Bera statistics reject the hypothesis of normality, while serial dependencies are indicated by the Ljung-Box statistics.

Asymmetric and leptokurtic distributions are observed also in the day-ahead price returns (Panel (b) of the table), tallying with the results from the Jarque-Bera and ARCH tests. This is in line with the one-month-ahead markets (Table 4.1 Panel (b)). Inferences based on the Ljung-Box statistics of the price return series are mixed but indicate higher degree of serial dependence in the day-ahead markets compared to the one-month-ahead markets. As expected, greater volatility is observed in the day-ahead markets compared to the one-month ahead, which is confirmed by pairwise F-tests for equal variance of the returns in the two markets.

Table 4.2: Descriptive statistics of the weekly medians of the daily day-ahead prices at different European hubs (Euro/MWh)and of their returns

	NBP	TTF	Zeebrugge	NCG	PEG North	PSV
Level (Euro/MWh)						
Mean	17.73	21.13	18.09	23.14	22.37	25.82
St.Dev.	4.796	5.324	4.678	3.588	4.156	3.997
Skewness	-0.385	-0.609	-0.573	-0.093	-0.195	-0.437
Kurtosis	3.06	2.99	3.07	3.78	3.24	2.669
Median	18.59	22.19	19.02	23.25	22.70	26.80
Min	5.64	7.40	5.53	13.40	11.72	14.65
Max	34.11	38.475	34.54	38.30	36.90	34.30
Jarque-Bera	0.015***	0.001***	0.001***	0.034***	0.208	0.020***
ARCH (20)	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Ljung-Box (20)	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
1st Obs	06/10/2008	02/01/08	02/01/08	28/03/2011	05/01/2010	07/07/2011
Obs.	386	426	426	255	319	241
Returns						
Mean	-0.0015	-0.0015	-0.0015	-0.0024	-0.0005	-0.0026
St.Dev.	0.071	0.066	0.072	0.045	0.052	0.037
Skewness	-0.459	-0.357	-0.463	-0.309	-0.277	-0.053
Kurtosis	7.480	8.400	8.286	7.848	13.270	5.345
Median	-0.0006	-0.0019	-0.0007	-0.0037	-0.0010	0.0000
Min	-0.3778	-0.3721	-0.3742	-0.2139	-0.3656	-0.1467
Max	0.3021	0.2847	0.2886	0.1883	0.2608	0.1508
Jarque-Bera	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
ARCH (20)	0.000***	0.000***	0.000***	0.000***	0.000***	0.003***
Ljung-Box (20)	0.047**	0.008***	0.004***	0.382	0.426	0.851
Obs.	385	425	425	254	318	240

In Figures 4.3 and 4.4, the weekly medians of the daily day-ahead prices at European hubs (Euro/MWh) and their returns are depicted, respectively. Co-movements between the price series can be observed (Figure 4.3), which are noticeable in February 2012 and in March 2013, when European markets were affected by supply constraints and unexpected lower temperature. Nonetheless, returns in Figure 4.4 suggest differences in price volatility dynamics across hubs, which are more pronounced at the PSV hub. Differences in price volatilities can be also observed between day-ahead and one-month-ahead forward markets (Figure 4.2). They indicate greater volatility in the day-ahead than in the one-month-ahead markets, thus corroborating descriptive statistics in Tables 4.1 and 4.2.

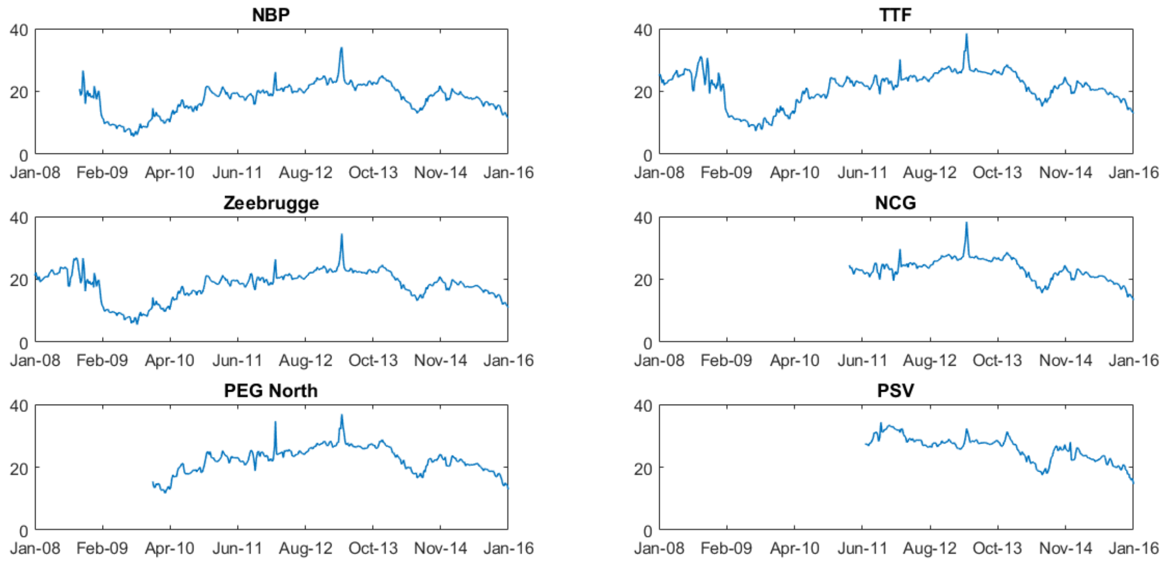


Figure 4.3: Weekly medians of daily day-ahead prices at European hubs (in Euro/MWh)

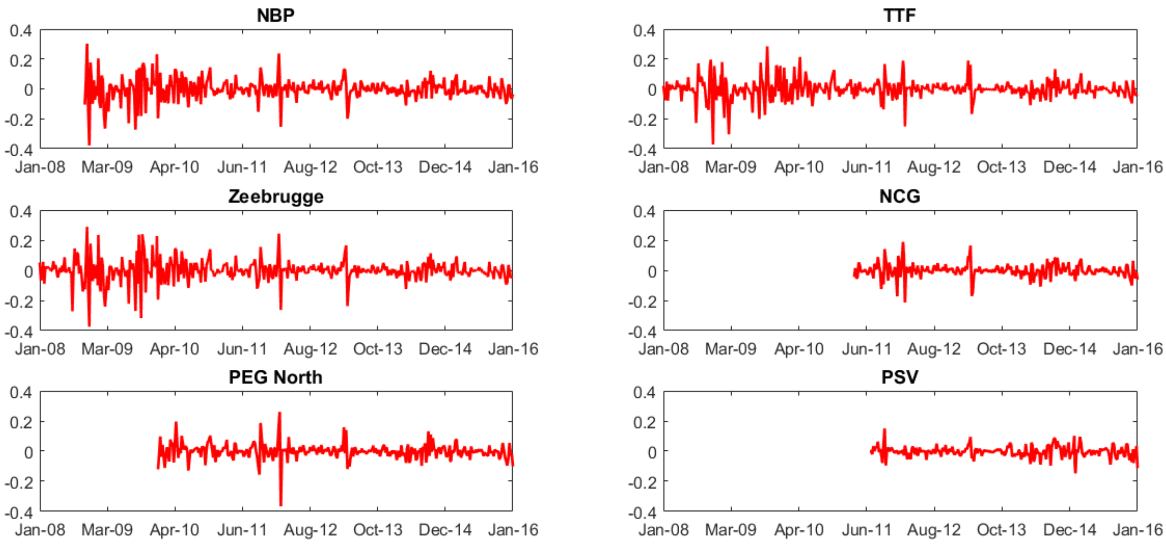


Figure 4.4: Returns of the weekly medians of daily day-ahead prices at European hubs

Descriptive statistics of the weekly medians of the daily one-month-ahead Brent crude oil and natural gas forward prices (in US dollar), adjusted at six-month lags are presented in Table 4.3 Panel (a). Their returns are described in Panel (b) of the table. The first four moments (Mean, Std.Dev., Skewness and Kurtosis) are reported in rows two to five. Median, minimum and maximum statistics are shown in rows six to eight. Rows nine-eleven presents the p-values of the Jarque-Bera statistics, Ljung-Box statistics and ARCH tests computed at the 20^{th} order of lags. The first observation of each series and the total number of observations are reported in rows twelve-thirteen of Panel (a), respectively.

In Panel (a) of Table 4.3, the Jarque-Bera statistic rejects the hypothesis of normality of the Brent crude oil price series. Asymmetries and ARCH effects are also observed in this series, whilst the Ljung-Box test rejects serial independence.

Asymmetries and leptokurtosis are observed in the distribution of Brent crude oil price returns in Panel (b) of Table 4.3. No significant differences can be observed in the distributions of the one-month-ahead natural gas forward prices and their returns, after converting prices in US dollar and adjusting the sample periods.

Table 4.3: Descriptive statistics of the weekly medians of the one-month-ahead daily Brent crude oil and natural gas forward prices and their returns (US dollar)

	Brent	NBP	TTF	Zeebrugge	NCG	GasPool	PEG North	AVTP	PSV
Panel (a): Prices									
Mean	93.15	16.19	16.23	16.18	16.38	17.85	16.20	18.78	20.30
St.Dev.	23.34	4.362	4.198	4.279	4.191	2.337	4.295	2.254	2.640
Skewness	-0.493	-0.658	-0.807	-0.758	-0.810	-0.636	-0.884	-0.968	-0.702
Kurtosis	2.20	2.77	2.84	2.83	2.85	2.519	2.72	3.016	3.450
Median	102.6	17.26	17.35	17.16	17.53	18.33	17.51	19.43	20.88
Min	38.37	5.39	5.63	5.43	5.60	11.372	5.69	12.200	12.78
Max	143.1	28.07	25.27	26.51	25.58	21.953	23.12	21.70	25.57
Jarque-Bera	0.001***	0.001***	0.001***	0.001***	0.001***	0.002***	0.001***	0.001***	0.002***
ARCH (20)	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Ljung-Box (20)	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
1st Obs	02/01/08	01/07/08	01/07/08	01/07/08	26/08/08	01/09/10	09/03/09	07/07/11	07/07/11
Obs.	400	400	400	400	392	285	363	241	241
Panel (b): Returns									
Mean	-0.0015	-0.0012	-0.0012	-0.0013	-0.0010	-0.0007	0.0007	-0.0011	-0.0012
St.Dev.	0.041	0.056	0.050	0.054	0.049	0.036	0.047	0.035	0.031
Skewness	-0.187	1.041	0.324	0.023	0.509	1.841	0.772	1.259	0.918
Kurtosis	7.366	10.575	6.682	9.354	7.808	14.531	8.773	14.766	7.085
Median	-0.0010	-0.0040	-0.0027	-0.0029	-0.0027	-0.0016	-0.0012	-0.0023	-0.0024
Min	-0.2018	-0.2617	-0.2024	-0.3266	-0.2206	-0.1232	-0.1996	-0.1840	-0.0803
Max	0.2010	0.3295	0.2133	0.2364	0.2291	0.2585	0.2440	0.2165	0.1744
Jarque-Bera	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
ARCH (20)	0.000***	0.040**	0.000***	0.006***	0.001***	1.000	0.014**	0.000***	0.477
Ljung-Box (20)	0.000***	0.016**	0.260	0.011**	0.099*	0.561	0.058*	0.115	0.082*
Obs.	399	399	399	399	391	284	362	240	240

In Figure 4.5, the weekly medians of the one-month-ahead Brent crude oil and natural gas forward prices are shown. Their returns are depicted in Figure 4.6. Similar dynamics are noticeable in the crude oil and natural gas price series in the period 2008-11. This period corresponds to when both crude oil and natural gas prices volatilities were high, as suggested by movements in the price returns (Figure 4.6). The link between Brent crude oil and natural gas prices reduces from 2012 onwards, as indicated in Figure 4.5.

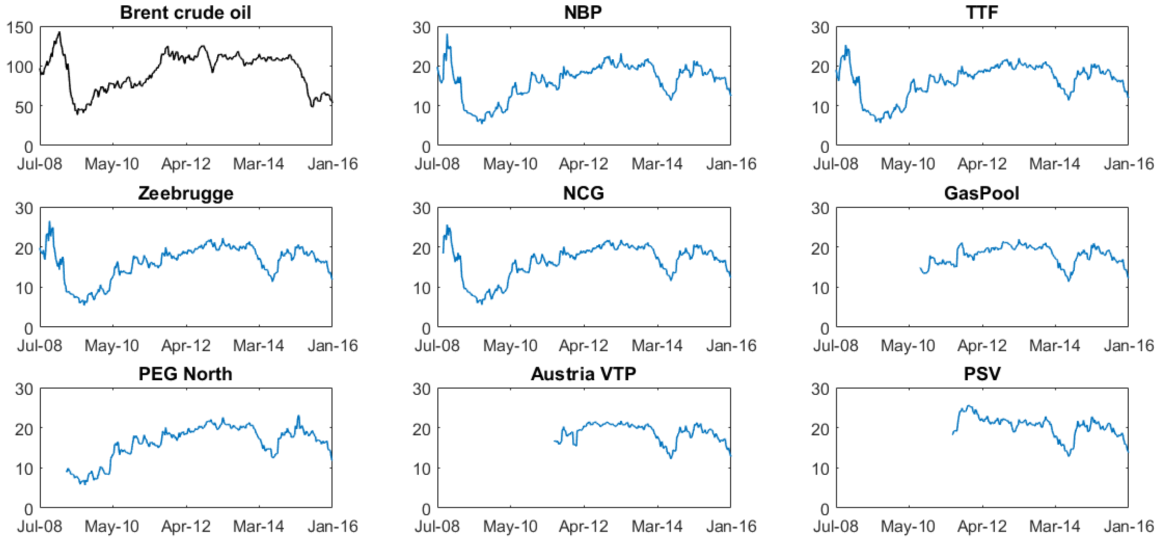


Figure 4.5: Weekly medians of the one-month-ahead Brent crude oil and natural gas forward prices (US dollar)

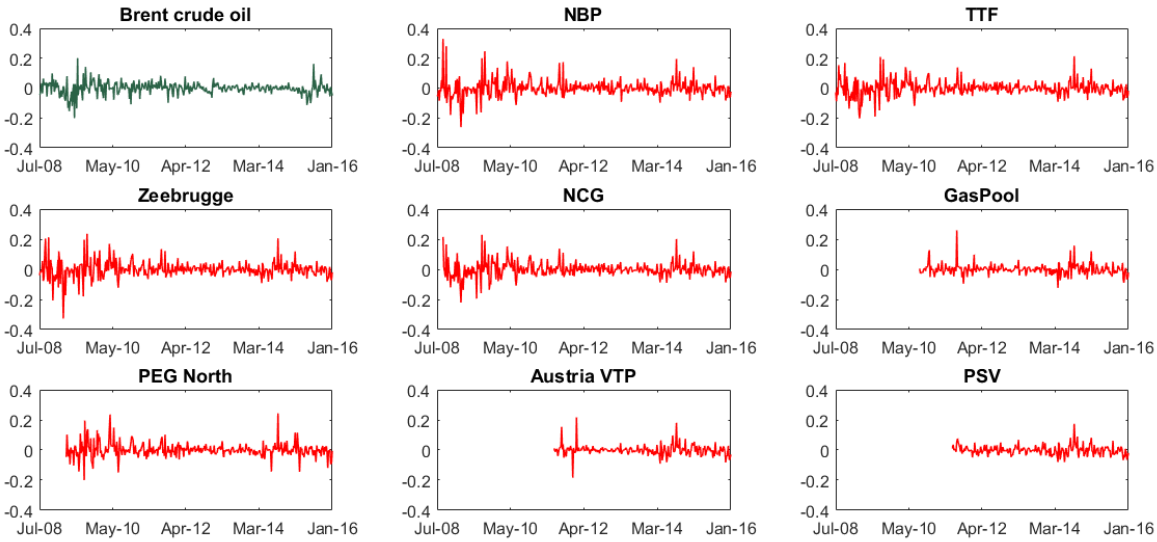


Figure 4.6: Returns of the weekly medians of the one-month-ahead Brent crude oil and natural gas forward prices

Overall, preliminary data analysis suggests some co-movements between natural gas prices at different European hubs, and between natural gas and Brent crude oil prices. Nonetheless, this analysis also highlights the time-varying feature of these co-movements. Differences in the volatilities between one-month-ahead and day-ahead are also significant, thus suggesting that different factors may explain price dynamics in the one-month-ahead and day-ahead markets and affect the market integration process. In the next section, results from the analysis of price convergence and market integration are presented.

4.6 Empirical Results

4.6.1 Price convergence in European natural gas markets

Pairwise estimates of the time-varying state variable m_t of the one-month-ahead forward prices are shown in Figure 4.7 (blue line), along with their 95% confidence intervals (red dots). Estimates have been carried out assuming as leading variable the most liquid and mature European hub, i.e. NBP (Cummins and Murphy, 2015; Petrovich, 2015), and prices in Euro/MWh.

Convergence can be inferred between the NBP and the Dutch TTF one-month-ahead price series, as well as between the NBP and the Belgian Zeebrugge series, since the estimated m_t are not statistically different from zero. A misalignment between the NBP, and the TTF and Zeebrugge prices can be noticed in September 2008, when the collapse of the natural gas demand mainly affected the NBP prices. Convergence is noticeable from 2009 onwards, when the TTF and Zeebrugge hub prices re-aligned to NBP, thus entailing high degree of connection within the markets in the period.

Convergence appears to be supported between the NBP, and the German NCG and GasPool one-month-ahead forward prices. Price misalignments are observed in the second half of 2011, in particular between the NBP and the GasPool, which may be linked to the merger of German market zones to create the current state of two markets, namely NCG and GasPool (Heather, 2015).

Convergence can be also inferred between the NBP and the PEG North prices. Some price misalignments are noticeable in the first half of 2014 and 2015, when forward prices declined sharply in Europe (Figure 4.1) and the natural gas French market suffered a downward trend in the arrival of LNG at its terminal, which widened prices difference with the British hub (Commission de régulation de l'énergie, 2014, 2015).

The Austrian AVTP hub price appears to be aligned to NBP, whilst misalignments are observed when the Italian PSV is considered. Results indicate a process towards price convergence in the Italian market, in particular from the second half of 2012 onwards, after some regulatory changes to promote trading at the PSV hub (Heather, 2015). Nonetheless, the estimated state variable indicates that natural gas at the Italian hub is traded at premium compared to the NBP price, thus implying constraints to the integration of the two markets.

On the whole, seasonal behaviours can be observed in the time-varying state variable m_t, which are mainly noticeable when convergence between NBP, and TTF, Zeebrugge, NCG and GasPool is considered and may affect the process towards integration in one-month-ahead forward markets.

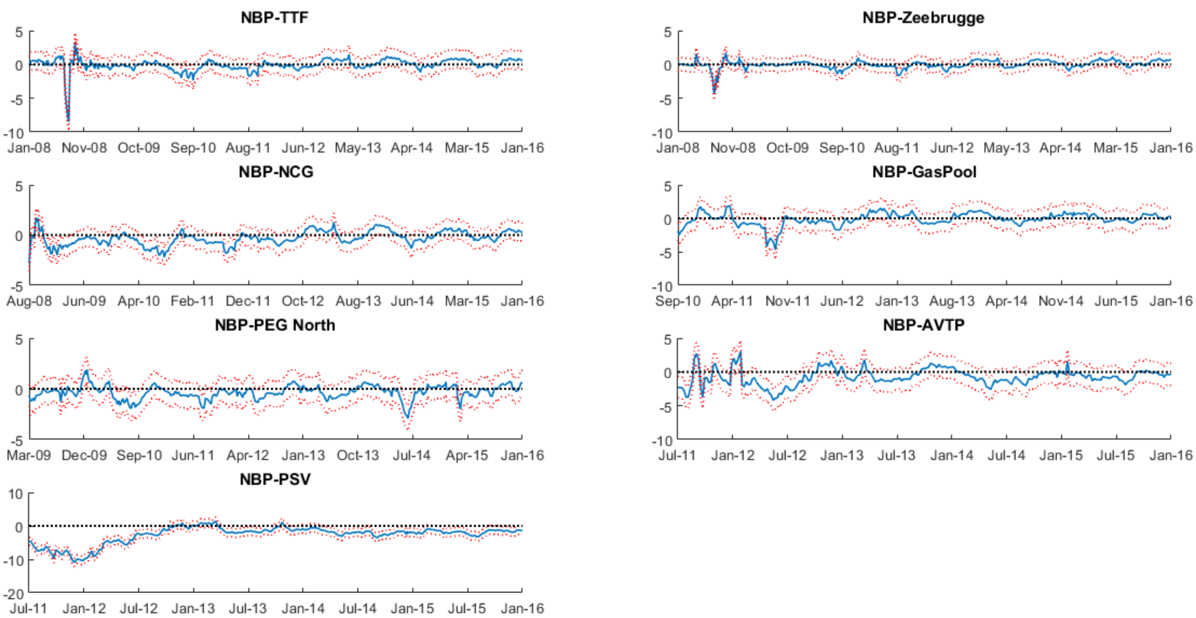


Figure 4.7: Pairwise estimates of the time-varying state variable m_t and their 95% confidence intervals: one-month-ahead forward prices (Euro/MWh)

In Table 4.4, the descriptive statistics of the estimated time-varying state variable m_t of the one-month-ahead forward prices in Figure 4.7 are presented. The first four moments (Mean, Std. Dev., Skewness and Kurtosis) are shown in rows two to five. Median, maximum and minimum values are reported in rows six to eight. The p-values of the Jarque-Bera statistics for the assumption of normality are given in row nine. The number of observations is shown in row ten.

Pairwise t-tests and non-parametric sign tests for equal means and medians indicate higher misalignment between the NBP and PSV hub prices, relative to other hubs in the period, thus corroborating suggestions from Figure 4.7. Higher price convergence is observed between the NBP and Zeebrugge prices. Overall, the estimated state variables m_t are asymmetrically distributed around their mean values, thus implying that time-varying dynamics affect the transmission system. Furthermore, statistics support some seasonal behaviours in the price convergence, as suggested by Figure 4.7.

Table 4.4: Descriptive statistics of the time-varying state variable m_t: one-month-ahead forward prices (Euro/MWh)

	TTF	ZEE	NCG	GPL	PEG North	AVTP	PSV
Mean	-0.050	-0.003	-0.301	-0.116	-0.331	-0.738	-2.704
Std. Dev.	0.933	0.599	0.687	0.938	0.663	1.222	2.615
Skewness	-3.823	-1.925	-0.169	-1.344	-0.433	-0.029	-1.414
Kurtosis	32.95	13.46	3.243	7.104	4.315	3.501	4.338
Median	-0.040	0.006	-0.326	-0.093	-0.286	-0.809	-1.900
Maximum	3.361	1.712	1.753	1.861	1.907	3.029	1.328
Minimum	-8.508	-4.323	-2.795	-4.706	-2.899	-4.187	-10.895
Jarque-Bera	0.000	0.000	0.242	0.000	0.000	0.278	0.000
Obs	426	426	392	285	362	241	241

Note: Estimates have been carried out assuming as leading variable the most liquid and mature European hub, i.e. NBP.

Pairwise estimates of the time-varying state variable m_t of the day-ahead prices (in Euro/MWh) are depicted in Figure 4.8 (blue line), as well as their 95% confidence intervals (red dots) and assume the NBP price as leading variable. Convergence can be inferred between Zeebrugge and NBP in the day-ahead prices, as suggested by their decreasing difference. By contrast, day-ahead prices at other Continental Europe hubs appear to be significantly higher than at NBP, as implied by negative differences.

Price misalignments are most noticeable in March 2013, when a cold spell combined with low storage levels in Northern Europe affected European natural gas markets. Nonetheless, increasing convergence can be observed between the NBP and Continental Europe hubs starting from the second half of 2015. This greater convergence might be explained by the increasing availability of spot LNG at European hubs as a consequence of the weak Asian gas demand, which coupled with a reduction in the oil-indexed contract prices due to the recent drop in the oil prices resulted in a downward price pressure in European natural gas markets (Timera-Energy, 2015a,b).

Notwithstanding the increasing convergence of the day-ahead natural gas prices at Continental Europe hubs, misalignments to the NBP price are still noticeable when compared to the one-month-ahead prices, thus entailing that day-ahead prices reflected unpredicted changes in the fundamentals of supply and demand differently and not simultaneously in the period considered. Consequently, higher price convergence may be inferred in one-month-ahead forward markets. In all, this implies that drivers of convergence in one-month-ahead and day-ahead markets are different, and are likely to affect market integration.

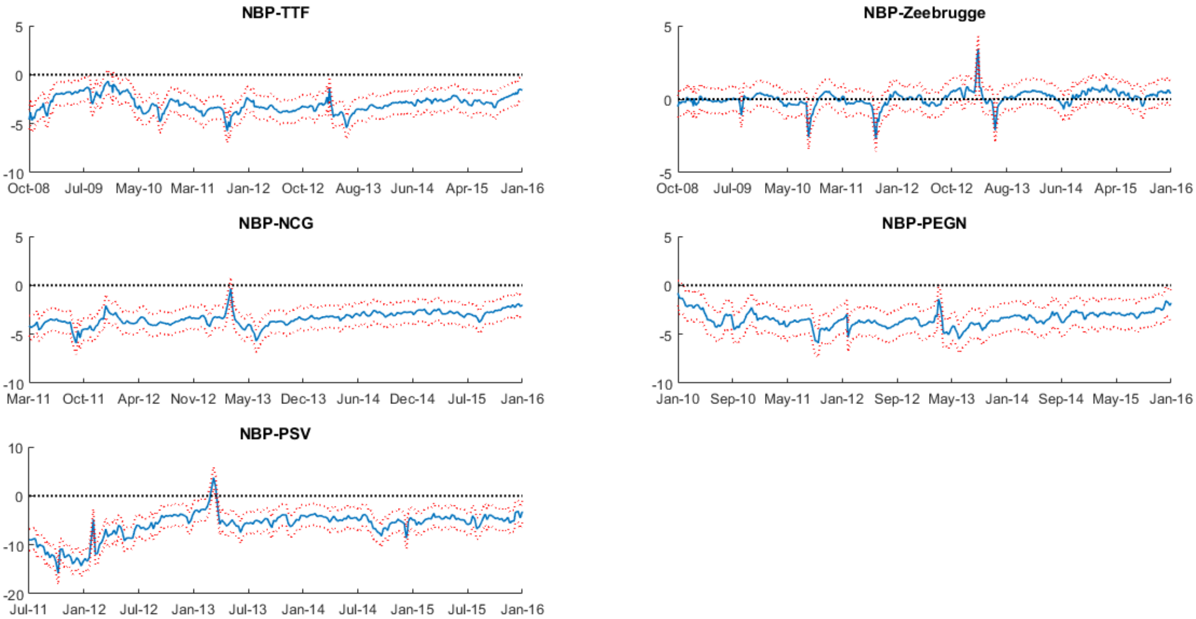


Figure 4.8: Pairwise estimates of the time-varying state variable m_t and their 95% confidence intervals: day-ahead prices (Euro/MWh)

Descriptive statistics of the estimated m_t of the day-ahead prices in Figure 4.8 are presented in Table 4.5. The first four moments (Mean, Std. Dev., Skewness and Kurtosis) are reported in rows two to five. Median, maximum and minimum values are shown in rows six to eight. Row nine reports the p-values of the Jarque-Bera statistics. The number of the observations in the sample is given in row ten.

In line with evidence from the one-month-ahead markets, the variables are asymmetrically distributed around their mean values, thus corroborating some seasonalities in the convergence process. Pairwise tests for equal means and medians indicate that price misalignments are greater in the day-ahead markets relative to the one-month-ahead markets and support Figures 4.7 and 4.8.

Table 4.5: Descriptive statistics of the time-varying state variable m_t: day-ahead prices (Euro/MWh)

	TTF	ZEE	NCG	PEG North	PSV
Mean	-2.980	0.055	-3.372	-3.455	-6.002
Median	-3.038	0.082	-3.345	-3.502	-5.164
Maximum	-0.672	3.447	-0.318	-0.780	3.698
Minimum	-5.748	-2.726	-5.907	-5.885	-15.837
Std. Dev.	0.837	0.530	0.720	0.778	2.856
Skewness	0.078	-0.411	-0.173	0.140	-1.025
Kurtosis	3.194	12.695	4.594	3.829	4.834
Jarque-Bera	0.607	0.000	0.000	0.006	0.000
Obs	386	386	255	319	241

Note: Estimates have been carried out assuming as leading variable the NBP.

Together the results indicate differences in the speed and magnitude of price convergence in the one-month-ahead and day-ahead markets. Results also suggest differences across hubs, which are mostly evident when the Italian PSV is considered and may affect the process towards a single market. In Section 4.7, the implications of these results for policy-makers, market players and researchers are discussed. In what follows, results from the cointegration analysis addressing integration within European natural gas markets and between natural gas and crude oil markets are presented.

4.6.2 Integration of European natural gas markets, and between European natural gas and crude oil markets

Natural gas markets integration: Evidence from the one-month-ahead and day-ahead markets

To support cointegration analysis, robust unit root tests were performed on the natural gas price series through ADF tests. The PLR statistics in Eq. (4.4) for the null hypothesis of unit root were computed through EM optimisation (Steps 1-2 of the procedure); their relative probabilities were thus obtained via bootstrapping (Step 3).

Results of the robust unit root testing procedure of the one-month-ahead forward prices (Euro/MWh) are summarised in Table 4.6. and indicate the non-stationarity of all price time series, as supported by the consistency of the PLR statistics and relative probabilities across lags and test specifications. Therefore, a pairwise cointegration analysis of the one-month-ahead forward prices was performed.

Table 4.6: Results of the robust unit root testing procedure: one-month-ahead forward prices

	NBP		TTF		Zeebrugge		NCG		GasPool		PEG North		AVTP		PSV	
Lags	PLR	Prob.	PLR	Prob.	PLR	Prob.	PLR	Prob.	PLR	Prob.	PLR	Prob.	PLR	Prob.	PLR	Prob.
Intercept																
1	3.546	0.243	2.210	0.548	2.656	0.363	3.067	0.496	0.391	0.936	1.805	0.539	0.093	0.986	0.032	0.995
2	3.241	0.258	2.239	0.540	2.127	0.433	3.217	0.489	0.380	0.934	2.151	0.480	0.146	0.981	0.063	0.989
3	3.391	0.249	2.638	0.488	2.525	0.382	3.583	0.467	0.590	0.897	2.591	0.433	0.051	0.992	-0.010	0.998
4	3.753	0.214	3.015	0.433	3.215	0.298	4.638	0.359	0.684	0.880	3.056	0.389	0.174	0.973	0.239	0.956
5	4.898	0.137	3.085	0.417	3.394	0.268	5.067	0.380	1.426	0.785	4.034	0.323	0.017	0.997	0.648	0.901
Trend and intercept																
1	4.438	0.216	2.110	0.595	2.576	0.424	3.620	0.550	2.318	0.584	0.350	0.947	2.885	0.477	5.952	0.231
2	3.976	0.252	2.089	0.612	1.991	0.505	3.763	0.537	2.357	0.567	0.539	0.919	3.145	0.460	5.099	0.288
3	4.081	0.236	2.465	0.556	2.381	0.440	4.179	0.520	2.771	0.533	0.721	0.872	2.713	0.489	4.786	0.300
4	4.526	0.207	2.870	0.488	3.096	0.333	5.348	0.396	2.962	0.527	1.218	0.764	3.307	0.436	6.669	0.215
5	5.509	0.152	2.841	0.486	3.171	0.332	6.141	0.415	4.182	0.450	1.587	0.665	2.617	0.487	8.736	0.139

Note: ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively.

The robust stepwise testing procedure in Section 4.4.2 was carried out assuming as leading variable the NBP series, thus in line with the state-space model above. Results of the pairwise cointegration analysis of the one-month-ahead forward prices are presented in Table 4.7. For each pairwise test, the PLR statistic in Eq. (4.4) for the null hypothesis H_0: Rank $\leq r$, $r = 0, 1$ against the alternative H_a: Rank $= 2$ is reported (after EM optimisation, as described in Steps 1-2), as well as its relative probability obtained trough bootstrapping (Step 3) and SIC.

PLR statistics fail to reject the null hypothesis H_0: Rank ≤ 1, i.e. cointegration, between NBP and TTF, Zeebrugge, PEG North and AVTP at all orders of lags. Cointegration is not rejected between NBP and NCG at first order of lags, and between NBP and GasPool at the first and second order of lags. Finally, cointegration is not supported between NBP and PSV at any order of lags. All in all, high integration can be inferred between the British and Dutch, Belgian, French and Austrian one-month-ahead forward markets. Integration is also supported between the British and German markets. By contrast, integration is rejected with the Italian market.

Table 4.7: Results of the pairwise robust cointegration analysis: one-month-ahead forward prices

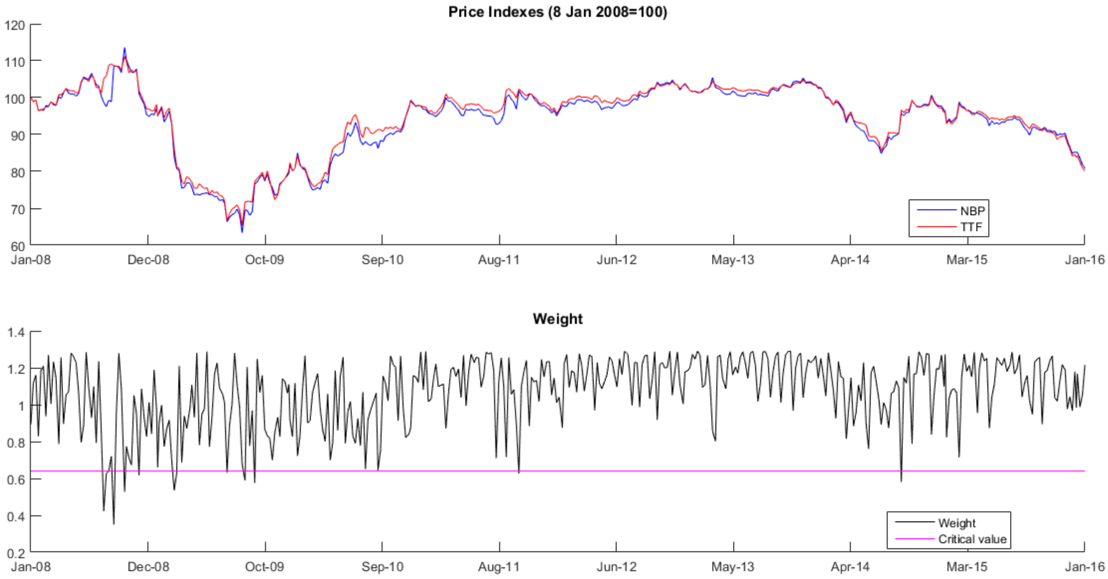
	1 lag			2 lags			3 lags		
$H_0 : Rank \leq$	PLR	Prob.	SIC	PLR	Prob.	SIC	PLR	Prob.	SIC
TTF									
0	57.36***	0.000	-13.41	51.73***	0.000	-13.38	50.69***	0.000	-13.33
1	2.31	0.828	-13.54	1.97	0.860	-13.49	2.28	0.826	-13.44
Zeebrugge									
0	42.36***	0.000	-13.68	34.01***	0.005	-13.69	39.86***	0.001	-13.64
1	2.55	0.796	-13.78	1.82	0.876	-13.76	1.99	0.880	-13.73
NCG									
0	35.75***	0.003	-13.91	20.60	0.197	-15.33	22.31	0.167	-13.89
1	3.47	0.664	-13.99	1.50	0.879	-15.39	3.81	0.670	-13.94
GasPool									
0	37.27***	0.001	-13.80	24.74*	0.082	-13.80	22.25	0.155	-13.73
1	3.11	0.734	-13.92	2.50	0.809	-13.88	2.73	0.774	-13.80
PEG North									
0	41.29***	0.000	-13.03	29.54**	0.011	-13.01	28.15**	0.021	-12.95
1	0.46	0.972	-13.14	0.59	0.959	-13.09	0.72	0.957	-13.03
AVTP									
0	36.84***	0.001	-13.65	27.71**	0.024	-14.36	27.34**	0.021	-13.55
1	1.43	0.912	-13.80	2.41	0.809	-14.38	1.78	0.876	-13.65
PSV									
0	10.30	0.871	-14.42	8.87	0.951	-14.36	8.37	0.961	-14.27
1	2.17	0.687	-14.45	2.36	0.666	-14.38	2.27	0.670	-14.30

Note: Results refer to the cointegration analysis as performed on a pairwise basis assuming as leading variable the NBP price. ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively.

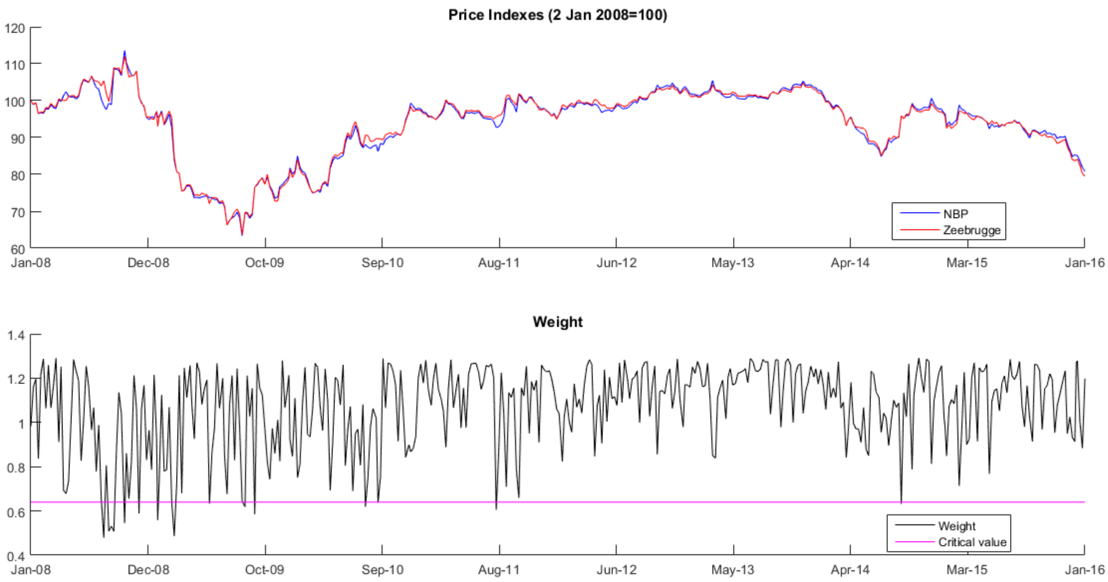
In Figure 4.9, the one-month-ahead price indices (top plots) are shown, which were obtained from the relative price increments by assuming as base the first available observation of the overlapping sample. On the bottom, the estimated weights in Eq. (4.7) and the 1% critical value (0.64) are depicted, which allow for the identification of periods of higher/lower integration between the considered markets. The weights are taken from the model specification in Eq. (4.3) that minimises the SIC statistics, as reported in Table 4.7.

The high level of integration between the NBP, and TTF and Zeebrugge one-month-ahead markets is entailed by their price dynamics (top plots) and by the empirical distribution of the estimated weights (Figure 4.9 (a)-(b)). This distribution tallies with that of the time-varying state variable m_t in Figure 4.7. Departures from the error-correction mechanism linking the NBP and the TTF and Zeebrugge price time series are observed in the second half of 2008, which are inferred from weights that are lower than the critical value, possibly corresponding to the slump of the NBP price, as mentioned above.

On the whole, some departures from the error-correction mechanisms are observed in the last quarter of 2014, which was characterised by mild temperatures, low industrial activity and high availability of LNG from the international markets. These factors may have nourished uncertainty in the one-month-ahead forward markets for the natural gas, thus leading to price misalignments and low market integration. Nonetheless, when the link between NBP and PSV is considered (Figure 4.7 (g) top plot), weights are less informative.

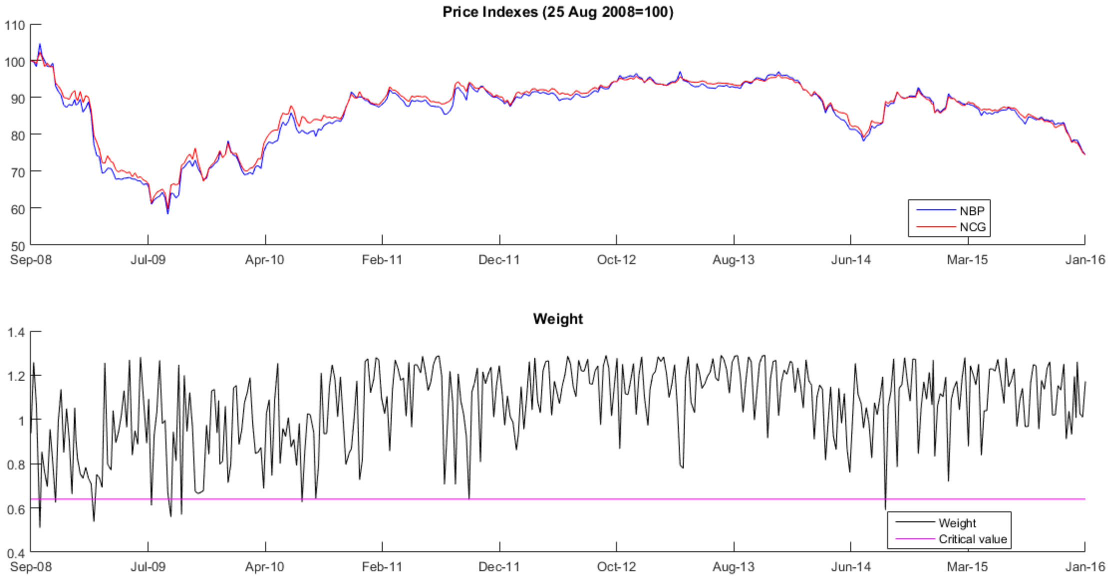


(a) TTF

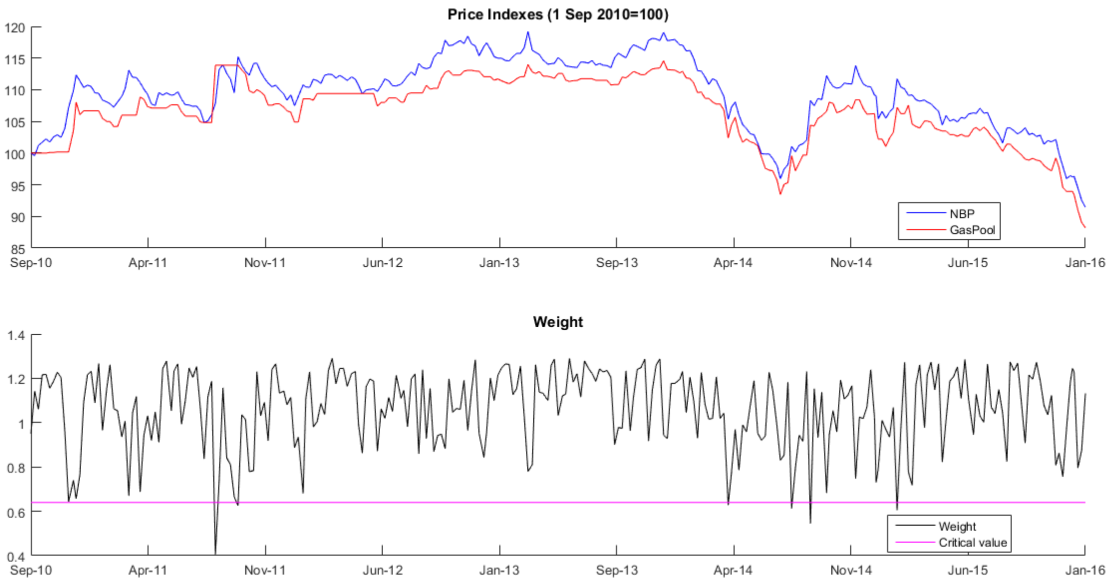


(b) Zeebrugge

Figure 4.9: Price indices (top) and weights (bottom) of the PLR statistics: one-month-ahead forward prices



(c) NCG



(d) GasPool

Figure 4.9: Price indices (top) and weights (bottom) of the PLR statistics: one-month-ahead forward prices (Cont.)

(e) PEG North

(f) AVTP

Figure 4.9: Price indices (top) and weights (bottom) of the PLR statistics: one-month-ahead forward prices (Cont.)

(g) PSV

Figure 4.9: Price indices (top) and weights (bottom) of the PLR statistics: one-month-ahead forward prices (Cont.)

Based on results of the cointegration analysis in Table 4.7, perfect integration was investigated in those markets where cointegration was observed. In particular, the restriction $\beta = -1$ in Eq. (4.3) was tested via the robust stepwise procedure described above and for order of lags where the hypothesis of cointegration was not rejected. PLR statistics and bootstrapped probabilities were then computed.

Results from the pairwise analysis of perfect integration in the one-month-ahead forward markets are presented in Table 4.8. With the exception of the Austrian ATVP market, where the restriction $\beta = -1$ is rejected at the 10% level of significance at the first order of lag, overall the PLR testing procedure supports perfect integration.

Table 4.8: Results of the pairwise perfect integration analysis: one-month-ahead forward markets

$H_0 : \beta = -1$	1 lag	2 lags	3 lags
TTF			
Intercept	0.067	0.065	0.057
α_1	-0.378	-0.350	-0.375
α_2	-0.141	-0.103	-0.119
β	-1.014	-1.014	-1.012
PLR	0.686	0.663	0.497
Prob	0.473	0.482	0.551
Zeebrugge			
Intercept	-0.004	-0.024	-0.031
α_1	-0.191	-0.284	-0.364
α_2	0.047	-0.07	-0.13
β	-0.993	-0.987	-0.985
PLR	0.248	0.734	1.225
Prob	0.667	0.474	0.367
NCG			
Intercept	0.128		
α_1	-0.274		
α_2	-0.080		
β	-1.023		
PLR	1.276		
Prob	0.323		
GasPool			
Intercept	0.095	0.019	
α_1	-0.117	-0.120	
α_2	0.154	0.1072	
β	-1.022	-1.001	
PLR	0.202	0.001	
Prob	0.680	0.984	
PEG North			
Intercept	-0.019	-0.020	-0.018
α_1	-0.087	-0.059	-0.069
α_2	0.215	0.2019	0.1983
β	-0.980	-0.978	-0.978
PLR	0.700	0.669	0.633
Prob	0.420	0.429	0.448
AVTP			
Intercept	0.599	0.589	0.593
α_1	-0.107	-0.079	-0.099
α_2	0.149	0.1478	0.144
β	-1.167	-1.163	-1.166
PLR	5.119*	3.514	4.018
Prob	0.062	0.174	0.133

Note: Results refer to the analysis performed on a pairwise basis assuming as leading variable the NBP price. ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively.

Together these results indicate high degree of price convergence and integration in the one-month-ahead forward markets. Nonetheless, integration appears to be stronger in North-West European countries compared to the Central-Southern, as implied by the cointegration analysis. The implications of these results for policy-makers and market players are discussed in Section 4.7.

Cointegration was also addressed in the day-ahead markets. Unit root tests, based on PLR statistics were performed on the day-ahead prices via ADF tests, as described above. Results after EM optimisation and their relative probabilities (from bootstrapping) are reported in Table 4.9. The non-stationarity of the day-ahead price time series is indicated by the PLR probabilities at all considered orders of lags and test specifications.

Table 4.9: Results of the robust unit root testing procedure: day-ahead prices

	NBP		TTF		Zeebrugge		NCG		PEG North		PSV	
Lags	PLR	Prob.	PLR	Prob.	PLR	Prob.	PLR	Prob.	PLR	Prob.	PLR	Prob.
Intercept												
1	3.923	0.239	4.783	0.203	4.800	0.136	1.506	0.694	4.930	0.170	0.280	0.961
2	2.559	0.408	3.039	0.344	2.813	0.258	0.492	0.902	4.060	0.231	0.023	0.996
3	3.375	0.271	2.545	0.417	2.718	0.258	0.168	0.965	2.649	0.326	-0.011	0.998
Trend and intercept												
1	4.189	0.241	4.808	0.232	4.830	0.149	4.778	0.207	4.296	0.206	6.544	0.208
2	2.715	0.379	2.953	0.367	2.708	0.285	2.682	0.396	3.410	0.285	4.887	0.289
3	4.432	0.239	2.389	0.448	2.586	0.299	2.136	0.475	2.123	0.396	5.082	0.261

Note: ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively.

Results of the pairwise robust cointegration analysis of the day-ahead prices, which assumes as leading variable the NBP price, are presented in Table 4.10. In the table, the PLR statistics in Eq. (4.4) for the null hypothesis H_0: Rank $\leq r$, $r = 0, 1$ against the alternative H_a: Rank $= 2$ are reported (after EM optimisation), along with their bootstrapped probabilities and SICs.

The hypothesis of cointegration with the NBP is not to reject in the case of TTF, Zeebrugge, NCG and PEG North at all considered orders of lags. By contrast, PLR statistics reject cointegration between NBP and PSV markets, which is in line with the results in the one-month-ahead markets. High integration is observed between the British and the

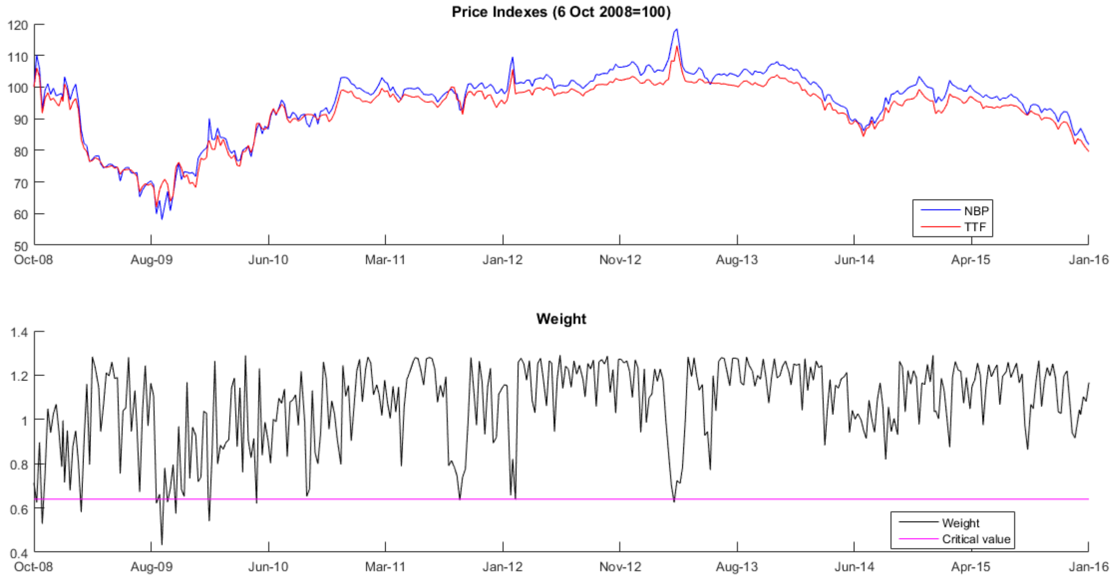
Dutch, Belgian and French markets, thus tallying with the results from the one-month-ahead markets. Some integration can be also inferred between NBP and NCG markets.

Table 4.10: Results of the pairwise robust cointegration analysis: day-ahead prices

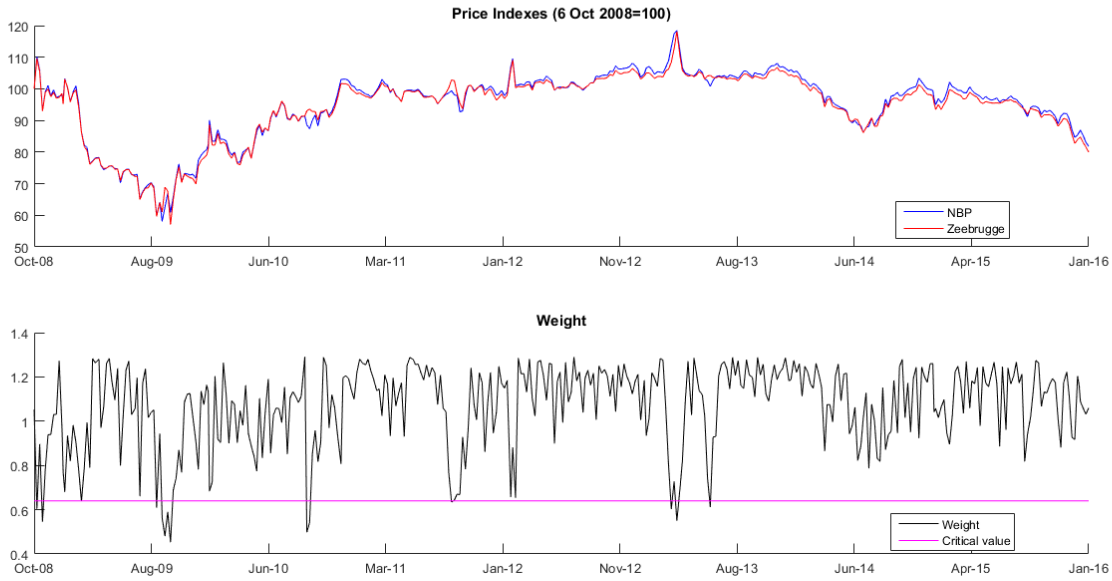
	1 lag			2 lags			3 lags		
$H_0 : Rank \leq$	PLR	Prob.	SIC	PLR	Prob.	SIC	PLR	Prob.	SIC
TTF									
0	47.16***	0.000	-12.06	52.00***	0.000	-12.09	41.63***	0.001	-12.14
1	3.82	0.629	-12.17	2.40	0.799	-12.22	2.77	0.787	-12.25
Zeebrugge									
0	69.87***	0.000	-12.64	43.13***	0.000	-12.73	35.72***	0.006	-12.768
1	3.98	0.601	-12.82	2.24	0.802	-12.84	2.98	0.754	-12.853
NCG									
0	39.67***	0.000	-13.52	37.56***	0.002	-13.48	24.34*	0.0998	-13.493
1	5.355	0.441	-13.65	2.58	0.788	-13.62	1.74	0.848	-13.583
PEG North									
0	49.78***	0.000	-12.96	42.03***	0.000	-12.93	37.05***	0.001	-12.891
1	4.38	0.572	-13.11	3.14	0.705	-13.05	2.29	0.804	-13.002
PSV									
0	20.37	0.171	-12.77	12.507	0.7304	-12.78	10.294	0.8844	-12.71
1	5.88	0.344	-12.83	4.0611	0.5798	-12.81	3.492	0.666	-12.74

Note: Results refer to the cointegration analysis performed on a pairwise basis assuming as leading variable the NBP price. ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively.

In Figure 4.10, the day-ahead price indices (top plots) and the estimated weights with their 1% critical value (bottom plots) are depicted, as described above. The weights are assumed from the model specification in Eq. (4.3) that minimises SICs (Table 4.10). The figure supports high integration between the NBP, and TTF, Zeebrugge, NCG and PEG North day-ahead markets (Figure 4.10 (a)-(d)). This is inferred by the price dynamics and by the estimated weights. Some departures from the error-correction mechanisms are observed during the cold spell in February 2012 and UK gas supply disruption in March 2013, which are indicated by estimated weights below the reported critical value (0.64). Overall, these results confirm the inference based on the state variable in Figure 4.8.

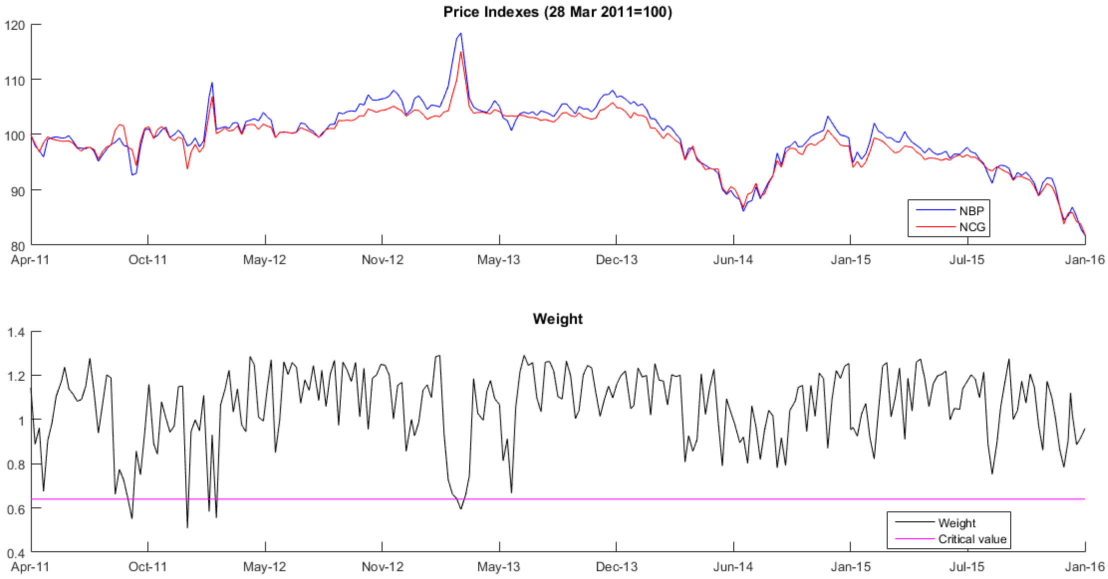


(a) TTF

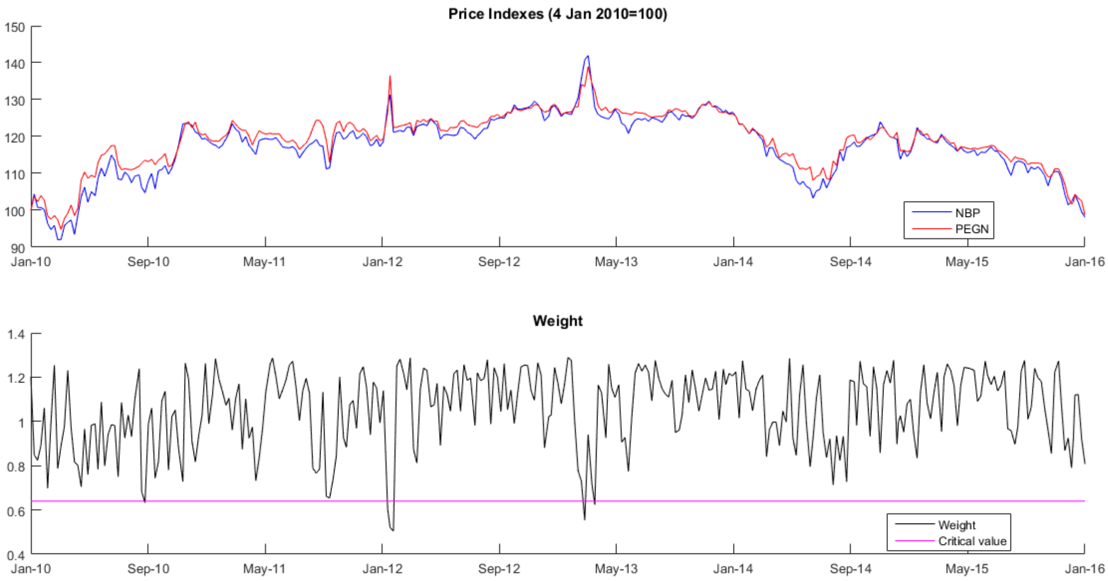


(b) Zeebrugge

Figure 4.10: Price indices (top) and weights (bottom) of the PLR statistics: day-ahead prices



(c) NCG



(d) PEG North

Figure 4.10: Price indices (top) and weights (bottom) of the PLR statistics: day-ahead prices (Cont.)

(e) PSV

Figure 4.10: Price indices (top) and weights (bottom) of the PLR statistics: day-ahead prices (Cont.)

Where in day-ahead markets cointegration with the NBP was observed (Table 4.10), the hypothesis of perfect integration (i.e. the restriction $\beta = -1$ in Eq. (4.3)) was tested through robust PLR statistics. Results from the pairwise analysis are presented in Table 4.11. PLR statistics fail to reject the hypothesis of perfect integration between the NBP and the TTF and Zeebrugge markets at all the considered orders of lags. Perfect integration is rejected between the NBP and NCG markets at the first and second order of lags, and at the 95% level of significance. Finally, perfect integration is not supported between the NBP and PEG North markets at 10% level of significance.

Table 4.11: Results of the pairwise perfect integration analysis: day-ahead prices

$H_0 : \beta = -1$	1 lag	2 lags	3 lags
TTF			
Intercept	0.249	0.267	0.237
α_1	-0.244	-0.200	-0.327
α_2	0.055	0.133	-0.015
β	-1.024	-1.030	-1.017
PLR	1.143	2.358	0.634
Prob	0.377	0.177	0.528
Zeebrugge			
Intercept	0.017	0.004	-0.009
α_1	-0.079	-0.160	-0.314
α_2	0.269	0.131	-0.050
β	-0.999	-0.995	-0.987
PLR	0.005	0.105	0.662
Prob	0.954	0.774	0.471
NCG			
Intercept	0.499	0.467	0.449
α_1	-0.117	-0.135	-0.125
α_2	0.205	0.213	0.169
β	-1.097	-1.088	-1.083
PLR	5.289**	5.116**	3.081
Prob	0.050	0.039	0.122
PEG North			
Intercept	0.375	0.379	0.351
α_1	-0.083	-0.108	-0.184
α_2	0.241	0.218	0.156
β	-1.051	-1.054	-1.052
PLR	3.436*	3.628*	3.332*
Prob	0.090	0.075	0.094

Note: Results refer to the analysis performed on a pairwise basis assuming as leading variable the NBP price. ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively.

All in all, results support integration within European natural gas markets. Nonetheless, integration appears to be higher in the one-month-ahead forward markets than in the day-ahead markets, and stronger in North-West Europe than in Central-South Europe. The implications of these results for the process towards a single European natural gas market and the overall efficiency of European energy system are discussed in Section 4.7. The integration between crude oil and natural gas markets is addressed below.

Integration between natural gas and crude oil markets

Robust unit root tests were performed on the one-month-ahead Brent crude oil forward price time series to ascertain its non-stationarity. Results are summarised in Table 4.12.

Non-stationarity can be inferred to characterise the crude oil price time series at all considered orders of lags and test specifications, thus justifying the cointegration analysis between natural gas and crude oil prices.

Table 4.12: Results of the robust unit root testing procedure: Brent crude oil prices

	Brent	
Lags	PLR	Prob.
Intercept		
1	1.1862	0.748
2	1.7284	0.6114
3	2.8523	0.4044
4	2.4634	0.4570
5	2.8224	0.4078
Trend and intercept		
1	0.9692	0.7980
2	1.472	0.6838
3	2.5808	0.4666
4	2.2444	0.5128
5	2.5702	0.4582

Note: ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively.

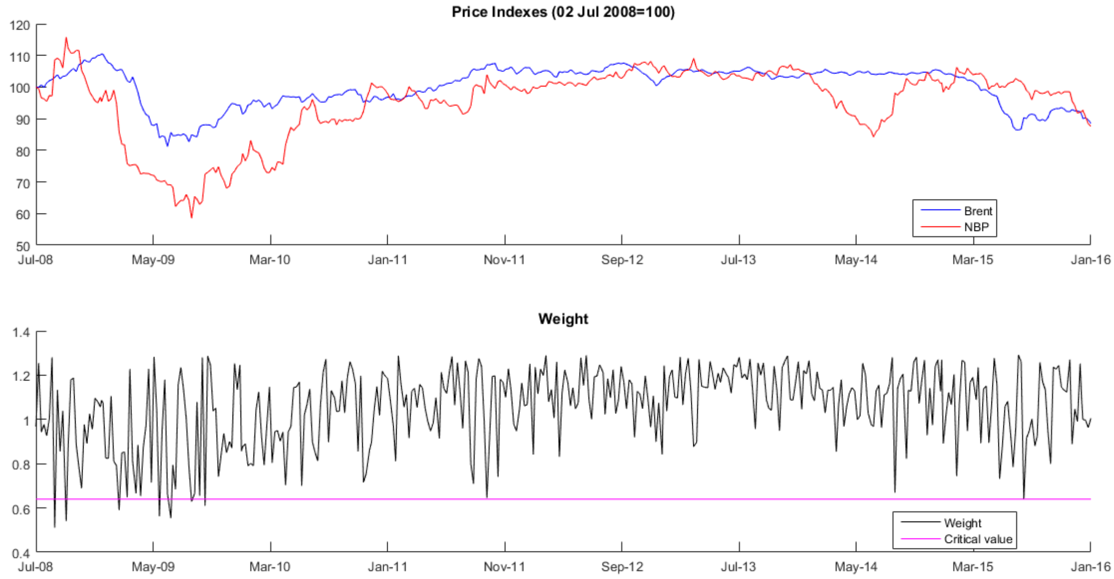
Cointegration analysis was performed on a pairwise basis assuming Brent as leading variable. Results of the stepwise procedure are reported in Table 4.13, where the PLR statistics in Eq. (4.4) for the null hypothesis H_0: Rank $\leq r$, $r = 0, 1$ against the alternative H_a: Rank $= 2$ (after EM optimisation) are presented, likewise their bootstrapped probabilities and SICs. The hypothesis of cointegration between natural gas and crude oil price time series is rejected at all considered order of lags, as suggested by bootstrapped probabilities.

Table 4.13: Results from the pairwise robust cointegration analysis: one-month-ahead natural gas and Brent crude oil forward prices

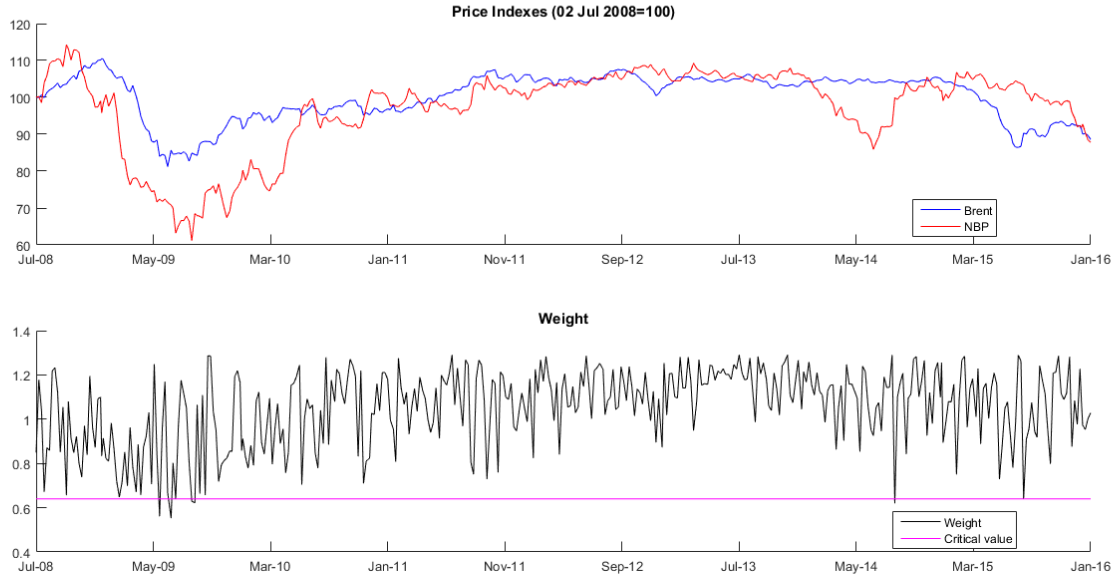
	1 lag			2 lags			3 lags		
$H_0 : Rank \leq$	PLR	Prob.	SIC	PLR	Prob.	SIC	PLR	Prob.	SIC
NBP									
0	14.34	0.531	-12.16	14.92	0.459	-12.12	16.77	0.327	-12.08
1	0.94	0.951	-12.20	1.19	0.928	-12.15	1.88	0.861	-12.12
TTF									
0	13.74	0.549	-12.40	13.12	0.602	-12.37	15.62	0.373	-12.33
1	0.88	0.952	-12.43	0.97	0.931	-12.40	1.51	0.877	-12.36
Zeebrugge									
0	14.75	0.487	-12.21	14.10	0.525	-12.18	16.74	0.315	-12.14
1	0.80	0.962	-12.25	1.11	0.930	-12.21	1.66	0.877	-12.18
NCG									
0	15.00	0.506	-12.45	14.96	0.519	-12.41	18.44	0.247	-12.38
1	1.15	0.940	-12.48	1.61	0.892	-12.44	2.11	0.824	-12.42
GasPool									
0	7.19	0.978	-13.60	8.05	0.954	-13.52	9.19	0.899	-13.44
1	0.47	0.969	-13.62	0.59	0.960	-13.54	0.82	0.949	-13.47
PEG North									
0	12.80	0.633	-12.47	12.88	0.591	-12.45	13.39	0.531	-12.44
1	0.00	0.999	-12.51	0.09	0.991	-12.48	0.29	0.974	-12.48
AVTP									
0	9.12	0.900	9.12	8.67	0.933	-13.64	8.69	0.940	-13.55
1	1.78	0.855	1.78	2.48	0.733	-13.66	2.92	0.661	-13.57
PSV									
0	10.49	0.813	-14.02	10.57	0.820	-13.93	11.14	0.766	-13.84
1	3.10	0.667	-14.05	3.74	0.572	-13.96	4.15	0.487	-13.86

Note: ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively.

Figure 4.11 shows the one-month-ahead natural gas and Brent crude oil price indices (top plots) and the estimated weights (bottom plots) which minimise SICs in Table 4.13. Results indicate that de-links between natural gas and Brent crude oil price series occurred over the period 2008-09, during the global economic downturn, when both natural gas and crude oil prices collapsed (Figure 4.5). These dynamics are noticeable when cointegration between Brent crude oil and natural gas prices at NBP, TTF, Zeebrugge and NCG hubs is considered, which are indicated by estimated weights below their critical value 0.64. Overall, a de-linking between crude oil and natural gas prices is observed over the period 2014-15, which was characterised by declining crude oil prices and high availability of LNG from the international markets.

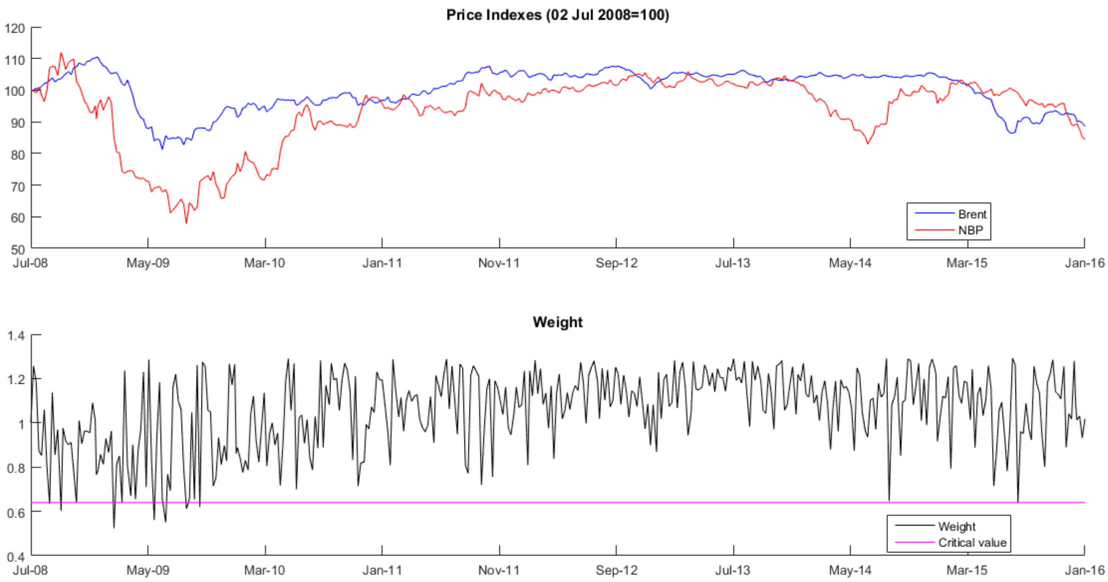


(a) NBP



(b) TTF

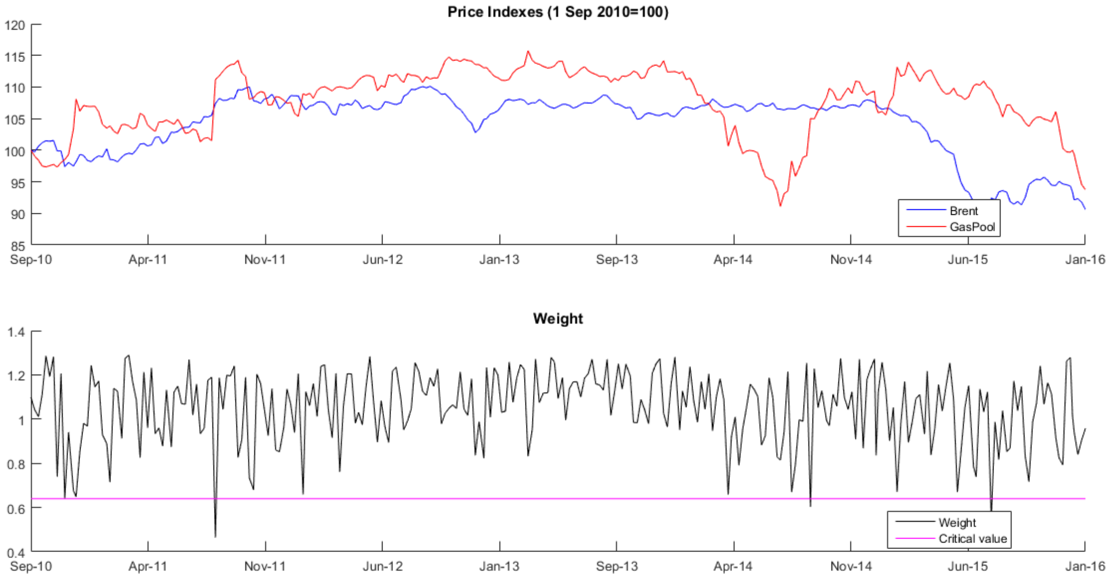
Figure 4.11: Price indices (top) and weights (bottom) of the PLR statistics: one-month-ahead natural gas and Brent crude oil forward prices



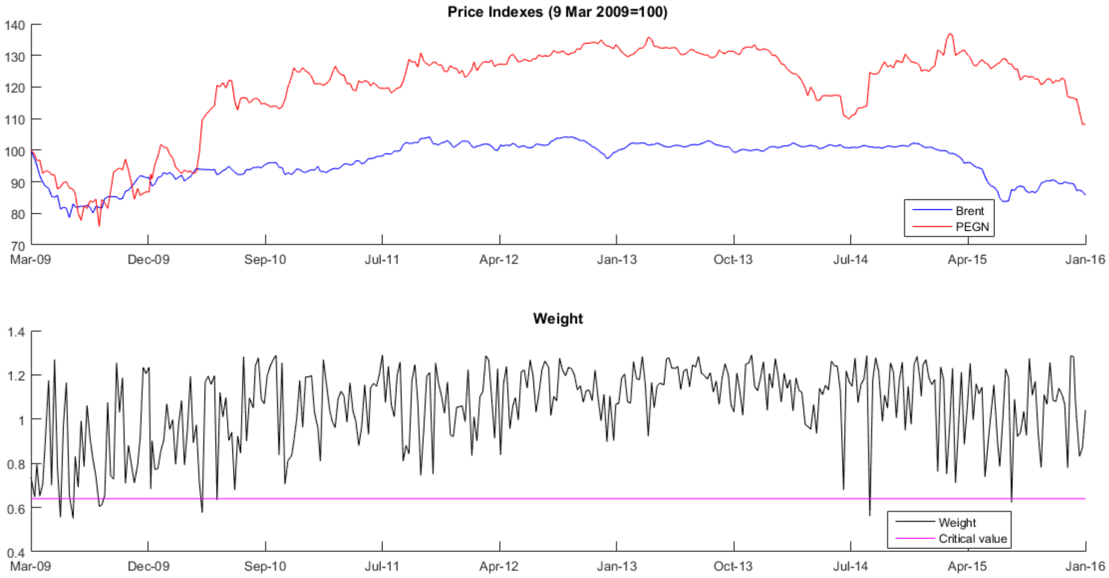
(c) Zeebrugge

(d) NCG

Figure 4.11: Price indices (top) and weights (bottom) of the PLR statistics: one-month-ahead natural gas and Brent crude oil forward prices (Cont.)

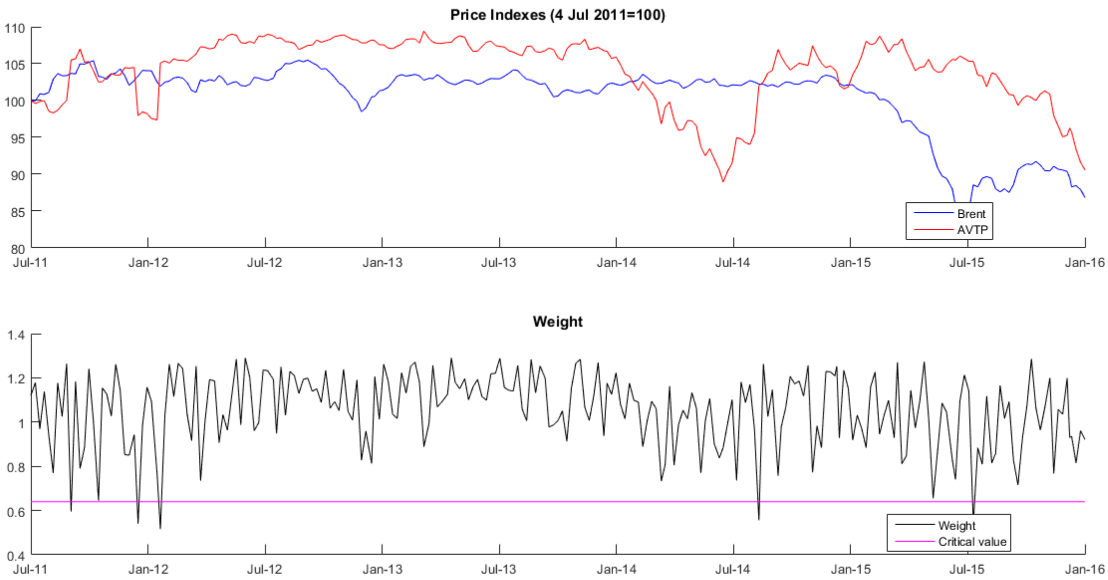


(e) GasPool

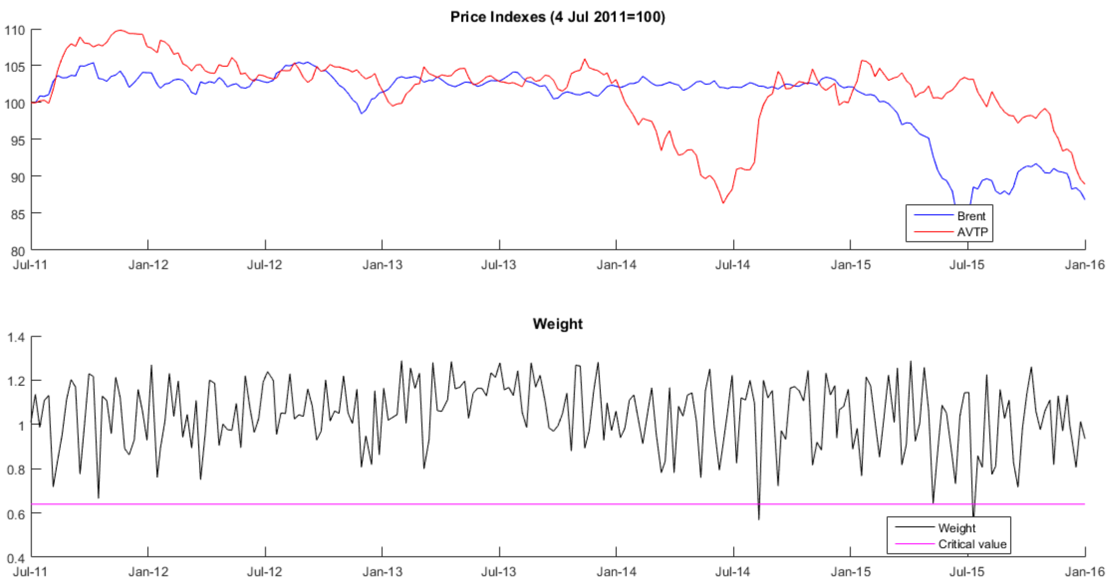


(f) PEG North

Figure 4.11: Price indices (top) and weights (bottom) of the PLR statistics: one-month-ahead natural gas and Brent crude oil forward prices (Cont.)



(g) AVTP



(h) PSV

Figure 4.11: Price indices (top) and weights (bottom) of the PLR statistics: one-month-ahead natural gas and Brent crude oil forward prices (Cont.)

On the whole, the stepwise cointegration analysis rejects the hypothesis of integration between natural gas and crude oil markets. In particular, there are indications that the most recent financial crisis and economic downturn, coupled with the high availability of LNG from international markets and decreasing natural gas and crude oil prices have undermined the traditional link between these two prices. In the absence of a *S-curve* in European markets (Timera-Energy, 2013), setting natural gas prices at a fixed fraction of oil prices in a midrange, but leaving the slop flatting and the intercept shifting at extreme oil prices, results in this study would support a move away of European natural gas prices from oil-indexation towards hub pricing, thus emphasising the role of the fundamentals of demand and supply as drives of the natural gas pricing mechanism in Europe.

4.7 Discussion

State-space models and robust cointegration testing procedures were used to address price convergence in European natural gas markets and ascertain their degree of integration over the period January 2008 - January 2016. Integration was found to be stronger within North-West European markets - United Kingdom, the Netherlands, Belgium and, to some extent, Germany - relative to Central-Southern markets - France, Austria, Italy -, which supports some previous research (Neumann and Cullmann, 2012; Renou-Maissant, 2012; Miriello and Polo, 2015; Heather, 2015; Petrovich, 2015) and market players (European Federation of Energy Traders, 2015). Compared to previous research, however, in this chapter differences were documented in the degree of integration between one-month-ahead and day-ahead markets, thus implying that different factors may prevent or foster the process towards a single market. It is noteworthy that, with respect to some previous research (Asche et al., 2001, 2002; Siliverstovs et al., 2005; Neumann et al., 2006; Renou-Maissant, 2012; Growitsch et al., 2015; Kuper and Mulder, 2016), results in this chapter are based on a robust cointegration stepwise procedures.

Differences in the degree of price convergence reflect in the transmission system functioning, which in this chapter was proxied by the state variable m_t (Figures 4.7 and 4.8). On the whole, convergence was found to be higher between the NBP, and the TTF and Zeebrugge prices, and this was observed in both one-month-ahead and day-ahead markets. Results therefore imply some structural integration within the British, and the Dutch and Belgian natural gas markets.

As observed in Chapter 1, trading activity is highly concentrated at the NBP and TTF hubs, where traded volume is almost one order of magnitude greater than at others European hubs. Although higher traded volume and liquidity may not be sufficient to guarantee price convergence (ACER, 2015b), results in this study indicate that, in one-month-ahead forward markets, the greater efficiency and liquidity of NBP and TTF hubs might have fostered their integration. Nonetheless, the observed integration between the British and the French and Austrian markets implies that NBP behaved as a referential market, able to drive price convergence in less competitive and liquid markets, which were more recently established, and where high degree of hub trading activity and liquidity have not been recorded yet (Chapter 1, Figure 1.1). Therefore, the results of this chapter would imply that the integration of one-month-ahead forward markets might be driven by financial trading and risk management through spread trading across hubs rather by the simple physical capacity. This would be in line with what suggested by Bunn and Gianfreda (2010) in European electricity markets.

As far as day-ahead markets are concerned, price shocks transmissions were observed in March 2013, when a cold spell and the UK gas supply disruption affected European natural gas markets and price misalignments were observed overall at their hubs. This would appear as an inefficiency of the markets because they need integration mainly during unexpected supply/demand changes and high seasonal demands to avoid abrupt price changes and volatility. Price misalignments to NBP were observed at PEG North hub in the second quarter of 2013, when capacity restrictions on the French network were recorded at the same time as a tight natural gas supply, following the sudden interruption of the UK gas supply. By contrast, a progress towards the alignment of the two prices was observed in the second half of 2014 (Figures 4.8 and 4.10), following a reduction of the network congestion after the increased availability of LNG at the Fos-sur-Mer terminal (Commission de régulation de l'énergie, 2013).

Price misalignments were also observed between the NBP and PSV price series, in both one-month-ahead and day-ahead markets (Figures 4.7 and 4.8). Under-utilisation of the transmission capacity connecting Italy to North-West Europe has been observed, which mostly reflects contractual capacity constraints (Miriello and Polo, 2015; Timera-Energy, 2016), thus impeding the integration of the Italian gas system (Tables 4.7 and 4.10).

Together, these results imply that network factors, such as inefficiencies in the capacity management and allocations, or different charges for transporting gas through transmission systems, may prevent market players from exploiting arbitrage opportunities within markets, in particular in the presence of unpredicted changes in the fundamentals of supply and demand, thus hampering price harmonisation at European natural gas hubs, mainly in day-ahead markets. Furthermore, high integration in day-ahead markets was mostly observed in geographically closer markets: UK, the Netherlands, Belgium. Therefore, it can be inferred that, when day-ahead markets are considered, which are more exposed to common shocks, the process towards a single market is more reliant on efficient demand/supply balancing mechanisms and physical transmission across intermediate markets.

Findings of this study have implications for the overall efficiency of European energy markets, mainly when the increasing integration between natural gas and power systems and the penetration of renewable sources would be considered, as for instance in Germany during the period April 2014 - April 2015. At that time, electricity generated from renewables, in particular wind, reached its peak to the detriment of gas (European Network of Transmission System Operators for Electricity, 2016). In the same period, price misalignments and departure from the error-correction mechanisms were suggested by the cointegration analysis, in particular at GasPool hub (Figures 4.9 and 4.10). Therefore, it can be expected that higher integration between natural gas and power sectors will affect the process towards a single European energy market. In this context, the efficient transmission capacity allocation in natural gas markets becomes crucial to manage demand/supply unbalancing, shocks to fundamentals and intermittent renewables production, and to guarantee stability in both natural gas and power markets.

The robust cointegration analysis in this chapter failed to find long-run relationships between Brent crude oil and natural gas forward prices, thus suggesting that price convergence in the European natural markets would be not supported by a common pricing mechanism driven by oil-indexation. This result is in contradiction with previous research (Rahman and Serletis, 2012; Hartley and Medlock, 2014; Asche et al., 2015), which however was based on traditional cointegration approaches. By contrast, the procedure implemented in this chapter assured the reliability of the results, in particular to periodical components and seasonalities that were suggested to affected the link between natural gas and oil prices (Asche et al., 2015). Nonetheless, results in this chapter do not exclude that oil-indexation may have affected hub pricing through the flexible component of ToP volumes, which is included in some long-term contracts (see Chapter 1). Depending on the competitiveness of gas hub prices relative to oil-linked gas contract prices, higher or lower volumes of flexible gas can be bought or sold at hubs than through long-term contracts. For instance, if hub prices are higher than oil-indexed prices, suppliers may find more convenient to sell the flexible volumes of gas at hubs rather than through long-term contracts; otherwise, when oil-indexed prices are higher than hub prices, buyers may find more convenient to purchase gas at hubs than through long-term contracts. This implies arbitrage opportunities between hub and oil-linked prices, which could explain some volatility spillovers between natural gas and oil prices, as observed in Chapter 3 of this dissertation. Nonetheless, these arbitrage opportunities appear insufficient to support integration between the two markets over the full period under investigation, as entailed by results in this chapter.

4.8 Conclusions and Further Research

The present chapter contributed to the existing literature price convergence and integration in energy markets by identifying different factors that may affect the process towards a single European natural gas market. In particular, the key research questions were the following:

1. Are European natural gas markets moving towards a single market? Are there differences between forward and day-ahead markets?

2. How is the link between natural gas and crude oil prices evolving in European markets? What are the implications for the integration process?

To address the first question, a pairwise approach was adopted to assess the degree of price convergence and integration between the British market, which was used as leading market, and the Belgian, Dutch, German, French, Austrian and Italian markets. Overall, integration was suggested between the British, and the Belgian, Dutch and, at some extent, German markets. This entailed high integration in North-West European natural gas markets. Lower integration was observed in the other markets. Differences in the degree of integration between one-month-ahead and day-ahead markets were also observed, which highlight some inefficiencies, mostly in the day-ahead markets.

Integration in one-month-ahead forward markets was mainly driven by NBP, which appears to be acting as referential hub for other European hubs. Players in European natural gas markets were suggested to consider price misalignments across hubs to exploit financial trading opportunities, despite the degree of liquidity at hubs. This would imply that liquidity is not necessary to drive integration in European natural gas markets. Nonetheless, liquidity is a barometer of market quality. Low liquidity entails high price volatility and transaction costs, and limited availability to trade, thus exposing internal markets to incumbent players, with implications for the continuing development of hubs and the competitiveness of European energy markets.

By contrast, day-ahead markets were found to be more exposed to physical transmission constraints and short-term demand and supply unbalancing, both in natural gas and power markets. This would appear as an inefficiency since markets need integration mostly to manage shocks to local demand or supply and curb energy price volatility. Low integration in the day-ahead markets could affect the stability of both European natural gas and power markets, in particular when greater penetration of renewable sources is assumed. Given the limited availability of hedging instruments at European hubs and their low liquidity, this would imply high price risk exposure and risk management costs, mainly for smaller market players, with strong implications for market competitiveness and quality.

It would also be cause of concern for regulators and policy-makers.

All in all, market integration was observed to be higher in North-West European countries than in the Central-Southern countries, thus indicating some inefficiencies in these markets hampering the exploitation of arbitrage opportunities among hub prices. Lack of price convergence and market integration was mainly evident in the Italian hubs, as suggested by the cointegration analysis, despite similar dynamics were entailed by the estimated weights across hubs. A follow-up study may therefore consider multivariate time series analysis and dummy variables accounting for costs and constraints in the transmission system, and indicating specific events in the markets, which could enable the identification of factors that impact short-term shock transmissions and price spreads across hubs, and may hinder market integration.

As far as the second research question is concerned, low integration was observed between crude oil and natural gas markets, which supports results in Chapter 3 and highlights the reliance of natural gas hub pricing mechanisms to the fundamentals of demand and supply. Nonetheless, since differences remain in the natural gas procurement mechanisms within European countries, misalignments across European gas hubs might be expected to persist. The persistence of these differences depends upon the extent to which European natural gas markets will adopt gas-on-gas competition, and may have implications for the pan-European energy market. These are factors that can be explored in further research.

Together, the findings in this chapter contributed towards understanding factors driving integration in European natural gas markets. In particular, physical constraints and local demand and supply factors were suggested to affect integration and price convergence over shorter-maturities, and mainly in Central-South European countries, which would nourish anticompetitive behaviours. This short-term dimension is of interest since it indicates that rules promoting capacity optimisation or adequate transmission allocation are required to allow for the efficient gas flow in response to price signals, and has implications for the process towards the EU's single energy market.

5

Summary and Conclusions

The main aim of this dissertation was to assess the current stage of the natural gas industry liberalisation process in Europe. In the view of the policy-maker, the liberalisation process and the development of a single European natural gas market were designed to foster efficiency in increasingly globalised markets. Nonetheless, this process has changed procurement mechanisms and market strategies of operators in response to the increasing role of hub prices as benchmarks and evolving regulatory framework, thus entailing new challenges for the energy sector. In this context, it was important to investigate liquidity, price volatility and market integration, since they affect hub prices and their behaviour, and are indicative of market quality and development towards the single energy market, as prescribed by several European directives and national policies in the last two decades. Therefore, a time-varying approach was adopted in this dissertation to properly suit the structural changes that have affected natural gas markets in Europe.

Chapter 1 focused on the process towards the liberalisation of European natural gas markets. The development of physical and financial trading at gas hubs, the evolving regulatory framework and price formation mechanisms were described. This chapter set the context of the research and explained the motivation for this dissertation.

In Chapter 2, liquidity dynamics in forward markets for natural gas were assessed using measures drawn from financial markets, which were found to capture well different dimensions of liquidity in the one-month-ahead NBP market. In particular, the modified time-varying measure of price impact enabled the estimation of the correlation between trading activity and price returns. In doing so, it allowed for inferences on the depth and resilience of the market that cannot be captured by the churn ratio, which is traditionally used to measure liquidity in energy markets. Thus, this measure of price impact is valuable to regulators when monitoring market quality, especially in the light of the comprehensive transaction data that following REMIT is now available to them. The availability of data can foster the development of market indicators and more detailed reports, which can further increase transparency. As a whole, the dynamics of the different measures of liquidity entailed improvements in market quality at the NBP and revealed correlations between trading activity, price volatility and liquidity. These findings support expectations from the financial literature on market microstructure and hint at drivers of quality in the natural gas markets. Nevertheless, implicit in the predictions of market microstructure theory is the "dark side" of liquidity: since it imposes transaction costs on market players, lack of liquidity creates instability and barriers to potential new entrants, as highlighted by the present findings. In addition, despite no significant change in liquidity following the entering into force of the new reporting obligations, there was evidence of a greater exposure of liquidity to unexpected price changes after REMIT. On the whole, Chapter 2 highlighted the strength of association between liquidity and price volatility, thus indicating that factors influencing price volatility can also contribute to explain market liquidity. Chapter 3 addressed drivers and dynamics of price volatility in the UK natural gas market. Volatility transmissions between natural gas and power markets were observed, suggesting high integration between the two markets. Consequently, given the high penetration of generation from intermittent renewable sources in the power sector, more volatile natural gas prices can be expected. Greater integration between carbon allowance and natural gas markets can be also expected, especially since the Carbon Price Floor that was unilaterally introduced by the UK Government in its Electricity Market Reform. In addition, dynamics in the correlation between natural gas and crude oil prices entailed lower integration between oil and gas markets, with implications for traditional hedging and risk management strategies that are based on the expectation of a strong correlation between the two prices. Indications were found of the predominance of fundamental values of demand, supply and inventory in driving price volatility in the UK natural gas market. Price volatility was found to be seasonal, as inferred by the NBP spot-futures prices spread, thus supporting the theory of storage. Dynamics of the spot-futures prices spread appeared to explain time-varying traded volumes in the futures markets under different market conditions, thus corroborating the positive correlation between price volatility and trading activity that was observed in Chapter 2. Therefore, the theory of storage also contributes to explain liquidity dynamics in the natural gas markets, and this is a valuable finding to those who are monitoring market quality. Although few spillover effects between natural gas and financial markets were found, results did not clarify the contribution of speculative trading as a source of price volatility in natural gas markets. Nonetheless, the general findings highlighted the role that changes in the stock indexes composition and market-capitalisation weights may have in explaining the relationship between financial and commodity markets.

In Chapter 4, European natural gas market integration was assessed and the evolving relationship between natural gas and crude oil prices was investigated. One-month-ahead and day-ahead natural gas forward markets were considered, and differences in the degree of integration within energy markets and across national markets were observed. Integration was found to be greater in the one-month-ahead relative to the day-ahead markets, thus suggesting physical constraints and high exposure of hub prices to local demand and supply factors, which can prevent integration. This can be interpreted as an inefficiency of European energy systems, since markets need integration mostly to manage possible physical outages and shocks to local demand or supply, and thus to curb energy price volatility. Low integration in the day-ahead markets can affect the stability of European natural gas and power markets, in particular when greater penetration of renewable sources is considered. Greater integration in the one-month-ahead markets might be driven by financial trading, despite the observed low level of liquidity across hubs (with the exception of the UK NBP and Dutch TTF hubs). Hence, liquidity is not a pre-requisite for integration within European natural gas markets. Nonetheless, liquidity remains a barometer of efficiency and market quality, as highlighted in Chapter 2. Low liquidity entails high price volatility and transaction costs, and limited trade, which facilitates incumbent players to assume dominant positions, thus hampering the overall competitiveness of European energy markets. In all, market integration was observed to be higher in North-West European countries than in the Central-Southern countries, thus indicating barriers to full integration. Low co-movement was observed between crude oil and natural gas markets, thus corroborating the findings from Chapter 3 and stressing the reliance of hub pricing mechanisms on demand and supply. Nonetheless, since differences remain in the natural gas procurement mechanisms within European markets, misalignments across European gas hubs are likely to persist, at least in the medium term. The extent of these differences relates to the predominant type of procurement mechanisms, whether hub trading or long-term contracts, and the penetration of gas-on-gas competition in all European markets. Therefore, these findings have implications for routine assessment of the competitiveness of the natural gas markets, and suggest obstacles in the process towards the EU's single energy market.

The main findings in this dissertation suggest some interesting future developments.

First, a full market integration is yet to be achieved, which is cause of concern for market designers and participants. The dynamics of liquidity in the NBP forward market during the period from May 2010 to December 2014 have provided warning signals, as they indicate potential entry barriers and large exposures to price variations in the UK. Although liquidity may not prevent market integration, decreasing liquidity can amplify the impact of physical constraints and infrastructural barriers, and thus affect the process towards price convergence at European hubs. Low liquidity reduces the ability of traders to realise temporal price arbitrage opportunities that are essential in more volatile and connected energy markets. Whilst liquidity issues are suggested in the findings, there are limitations to the analysis undertaken in this dissertation. The assessment of liquidity dynamics was restricted to the share of the market that was examined. In addition, the analysis focused on the most common forward contracts in Europe, namely those with a one-month-ahead maturity traded at the UK's NBP. As different dynamics might be entailed in forward prices at different hubs and maturities, extensions to this dissertation may investigate and compare liquidity dynamics across maturities and hubs. As observed in Chapter 2, the database did not allow to discriminate trade activity between market participants, and thus it was not possible to assess behaviours from commercial and non-commercial traders. With greater availability of data, additional indicators of market quality can be examined and compared. This is an avenue for future research, which could provide further insights in the relationship between different markets. Moreover, future studies should extend the period analysed in order to include data following REMIT's implementation (17 December 2015) and better clarify trading behaviour and market quality in European energy markets in face of an obligation to be fully transparent.

Second, the findings imply a decoupling of European natural gas prices from crude oil prices and greater integration between natural gas and power markets. The greater association with power markets has implications for the core objectives that are inherent in the EU energy policy, namely: energy security, energy affordability and environmental sustainability. Greater penetration of wind and solar power is expected to reduce electricity prices and increase price volatility in power markets, mostly in the intraday and day-ahead markets. Gas-powered generation increasingly faces higher price and volume risks, and will then require capacity payments and/or subsidies to compensate for low load-factors. Although increasing exposure of natural gas prices and volatilities to electricity generation mix was entailed by the findings in this dissertation, the analysis was limited to the UK market. An interesting development of this dissertation would be the investigation of the relationship between intermittent renewable power generation, natural gas and electricity prices and price volatilities across interconnected European markets. Results from this investigation could provide further insights to policy-makers, concerned about the flexibility and sustainability of European energy systems.

These topics are left to future research.

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