Information Transmission in Energy Futures Markets

A thesis presented

by

Sharon Xiaowen Lin

to

The Faculty of Finance
for the degree of

Doctor of Philosophy

in the subject of
Finance

City University Business School, London

Acknowledgements

I would like to thank my supervisors: Professor Costas Grammenos and Dr Michael Tamvakis, for their continuous guidance and encouragement to complete this thesis.

I am much obliged to Professor Mark Salmon, Professor Laurence Copeland, Dr Manolis Kavussanos and two external examiners: Professor Christopher Gilbert and Professor Colin Robinson, for their helpful comments and suggestions. Special thanks are owed to colleagues of the Centre, in particular, Dr Amir Alizadeh, Sam Dunmur, Sarah Dunmur, Mary Flynn, Gladys Parish and Marlene Stapleton for their assistance and encouragement over the years.

I am extremely grateful for my friends who have generously offered their support in many different ways. In particular I would like to thank Professor Michael de Harvilland, Dr Lili Cheng, Dr Xiaobing Feng, Dr Zhimin Tan, Shaun Ventham and Kevin X Yang.

Finally, I would like to thank my parents, my brother Steve and other family members: Uncle Ray, Aunts Lillian, Huilin, Lyn, Manlin and Linlin for their support and understanding over the difficult but important years of my life.

This thesis is dedicated to my parents and the memory of my grandmother Suzeng.

Abstract

Since the mid 1980s the world oil price discovery process has been dominated by two crude oil futures markets: the New York Mercantile Exchange (NYMEX) and London's International Petroleum Exchange (IPE). To date considerable work has been done to scrutinize the degree to which these two markets price efficiently, but little with regard to the way the two markets interact. It is the first attempt, to our knowledge, to investigate the interaction of the two markets. Given that participants in these markets move with relative ease from one market to the other and usually take positions in both of them, prices of these two leading crudes are kept closely related to each other. It is of interest, therefore, to investigate the speed of information transmission between IPE and NYMEX and, perhaps, identify which market is the true price leader.

To carry out this empirical investigation, simultaneous and non-simultaneous trading sessions of IPE and NYMEX are examined separately. Interesting findings are disclosed. Firstly, non-simultaneous trading sessions of IPE (IPE morning session) and NYMEX are analyzed with univariate and multivariate time series analysis respectively. In univariate analysis, spillover effects in mean returns are found in the IPE morning session from previous day NYMEX trading information, while no information transmission is found from IPE morning session to NYMEX same-day trading. In multivariate time series analysis with a larger data set, estimation using all data available suggests different results from that used in univariate analysis. However, closer analysis on sub-period estimation reveals consistent findings: the results from the first sub-period, which has the same observation data as in the univariate analysis, mirror those from univariate analysis; results from the second sub-period with extended data have a largely different behaviour from the first sub-period. It thus can be implied that the estimated results using all available information are averages of the behaviour of the two sub-periods.

This changing behaviour from one sub-period to the next points to a possible structural break between the two sub-periods. Given that there are no significant political forces, such as "oil shocks", taking place during the period under investigation, the changing forces must be coming from the markets themselves. Secondly, the simultaneous trading session of IPE and NYMEX is examined to detect the temporal lead-lag relationship between the two futures markets using 5-minute intervals. Results indicate a bi-directional relationship between the two, however the lead of NYMEX futures is dominant within 5-minute intervals. Further analyses under major news effects both on the supply side and demand side reveal: (1) the two markets move closer when there are major US news events taking place, and IPE is more efficient in information incorporation when there are major news events both on the supply and the demand sides; (2) the lead of NYMEX is stronger when there are major US events and that of IPE is stronger when there are major supply side events. Finally, intra-day trading activities of IPE are examined using the tick-by-tick transaction data. Empirical evidence from diurnal factor (intra-day seasonality), and from ACD model suggests that the patterns of IPE morning and afternoon durations are distinctively different from each other. These findings suggest that NYMEX has a large impact on IPE trading.

Empirical findings in this thesis imply that NYMEX is a leader in the information incorporation process, but the extent of this leadership changes dynamically; under different news effects as well as different time periods. These results would impose significant challenges to regulators, in today's global market, to keep their market competitive as well as prudent. They should also benefit hedgers, who after taking into account their hedging implementation criteria such as liquidity, may be able to benefit from the faster information transmission ability of the leading market by directly taking hedging positions using the leading market contracts. The users most likely to benefit from the above findings are traders, who may be able to take arbitrage profits after taking into account trading costs, borrowing costs, etc.

Abbreviations

c.i.f.	Cost, insurance and freight
EFP	Exchange of futures for physical
f.o.b.	Free on board IPE
IPE	International Petroleum Exchange
LOR	London Oil Reports
NYMEX	New York Mercantile Exchange
NYSE	New York Stock Exhchange
OSP	Official Selling Prices
SIMEX	Singapore International Monetary Exchange
WTI	West Texas Intermediate

Contents

List of Figures

List of Tables

Chapter 1
Introduction

Price discovery in crude oil and refined oil products has been extensively undertaken in organised futures markets for over a decade now. There are two dominant such markets today, the first one in the New York Mercantile Exchange (NYMEX) and the second in London's International Petroleum Exchange (IPE). With the weakening role played by OPEC as the price setter for crude oil since late 1980s, NYMEX light sweet crude and Brent crude .have usurped the role of benchmark grades for price setting. To date considerable work has been done to scrutinise the degree to which these two markets price efficiently, but little with regard to the way the two markets interact. Given that participants in these markets move with relative ease from one market to the other and usually take positions in both of them, prices of these two leading crudes are kept closely related to each other. It is of interest, therefore, to investigate the speed of information transmission between IPE and NYMEX and, perhaps, identify which market is the true price leader. This thesis is a first attempt to look at such a problem in the energy market. We believe that this empirical work is timely, given the ongoing globalization and deregulation of the energy markets. The uncovering of the potential market leader would have significant benefits to regulators, who are facing considerable challenge in regulating an increasingly global market; to traders who may take profitable arbitrage opportunities between the leading market and the lagging market;

and to hedgers who may be able to benefit from faster information transmission ability of the leading market by constructing a hedge at the leading market.

This thesis is organized as follows: Chapter 2 introduces IPE and NYMEX crude oil futures markets and their role in the world oil pricing system. It also discusses the interaction between the two markets, their physical linkages as well as the information linkages. This chapter sets the theoretical grounding on which further quantitative analyses can be carried out.

Chapter 3 reviews methodologies on lead-lag relationships in the existing literature and their relevance to our empirical analysis in later chapters; Chapter 4 examines the information transmission mechanism between NYMEX and IPE crude oil futures contracts in a univariate framework using daily data under both overlapping and non-overlapping trading hours. This chapter depicts general characteristics of the interaction between the two markets and points out directions for further investigation in the next three chapters. Chapter 5 concentrates investigation on the non-overlapping trading hours between IPE and NYMEX over time, while Chapters 6 and 7 conduct investigation on the overlapping trading hours between IPE and NYMEX with tick by tick, high frequency data. Five minute lead-lag relationships between the two markets are analyzed in Chapter 6 and durations between two transactions are examined in Chapter 7. Finally, Chapter 8 concludes.

This thesis contains a large portion of empirical work and some of the methodologies are being applied for the first time in the energy markets. Specifically, the use of duration analysis and high frequency lead-lag relationships is new to the markets under investigation, to our knowledge. The original contribution of the thesis pertains to the research aim - the speed of information transmission between IPE and NYMEX.

Chapter 2
Overview of world oil pricing system

"The world oil market, like the world ocean, is one great pool "

— Adelman (1984)

2.1 Introduction

Oil is the most actively traded commodity by volume[1] in the world. Total world trade in crude oil is over 33 mb/d (see Figure 2.1). Around 95% of the trade moves under term contracts from producing countries to importing nations. The remaining 5% is traded through established crude oil trading markets on a transaction by transaction basis. This latter trading mechanism ensures a market price discovery process through which a benchmark price is established. This benchmark price is then used as reference to price the majority of term contracts. Trading prices of various oil grades are adjusted up or down as a differential against a marker crude according to their quality contents. This market (marker crude) related formula has been widely accepted since 1986. The two most prominent such "marker crudes" are Brent Blend and West Texas Intermediate (WTI) which are established in UK and US respectively. Brent Blend is essentially an internationally exported crude, while WTI is a domestic US crude. Both

[1] In 2000, total volume of trade for grain (cereal & rice) and crude oil and crude oil are 295MT and 1661MT respectively. Total value of trade for grain (cereal & rice) and crude oil are 42b$ and 1025 b$ respectively. *Source: UN Food and Agriculture Organization and BP Statistical Review of World Energy.*

crudes have their own price discovery process, i.e. spot, forward and futures markets and are also related by physical delivery and trading.

This chapter aims to introduce the oil price discovery system, the role of WTI and Brent futures in the pricing system and the link between the two. Section 2.2 of this chapter looks at the world oil market and its pricing system. Section 2.3 looks at the two futures markets in detail and discusses the linkages between the two.

2.2 World oil markets and their pricing system

This section is organized as follows: Section 2.2.1 introduces world oil markets in relation to the time horizon: spot markets, forward markets and futures markets; Section 2.2.1 briefly examines the history of oil price formation - from price setting to market pricing; Section 2.2.2 illustrates the price reporting and transmission system.

2.2.1 World oil markets

The World oil market consists of spot, forward and futures markets. Each constituent market has different functions and is an integral part of the world oil market. Each market will be briefly discussed below:

World oil spot markets

A spot price is quoted on the basis of one-off, arm's length deals, usually to be delivered within a month.

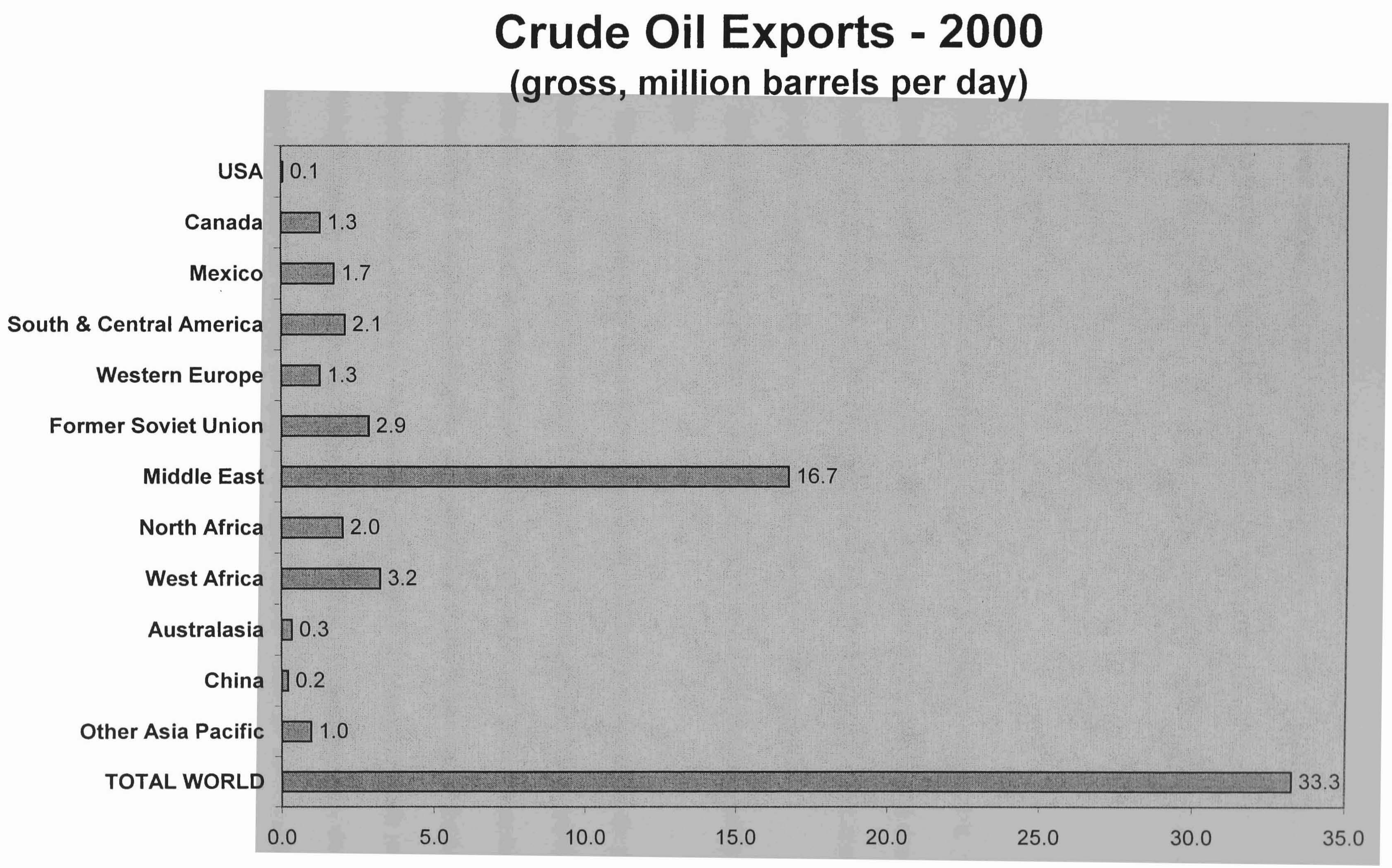

Figure 2_1 Crude Oil Exports (2000)

Current trading and price formation of physical oil spot prices will be briefly discussed in this section. The organisation is based on producing area, firstly the North Sea, followed by the US, West Africa, the Mediterranean, the Middle East Gulf, and the Far East.

The North Sea

The North Sea production is dominated by the UK and Norwegian sectors. UK production amounted to 2.66 mb/d in 2000. Norwegian sector activity surpassed that of UK in 1991 and its production in 2000 reached 3.36 mb/d. The most important contribution of the North Sea is the existence of the marker crude - Brent Blend.

Brent Blend is denominated as a light, sweet crude, with a specific gravity of 38° API.

The crude oil stream that currently makes up Brent Blend is a mixture of the production from a number of separate oil fields, collected through two distinct pipeline systems (the Brent and the Ninian systems) which carry the crude oil to the terminal at Sullom Voe in the Shetland Islands. The ownership of the producing oil fields of the Brent and Ninian systems is widespread. The number of companies with interests in both systems is approximately 33, but the ownership varies considerably due to takeover activities. The leading companies are Shell, Exxon Mobil, BP and Total Fina Elf, which account for about 75% of total entitlements. Not all companies are actively involved in the day-to-day operation of the fields. There are just over 8 companies operating the fields, all on behalf of other owners. The diversity of international own-

Crude	Origin	Gravity	Sulphur %
Brent	UK	37.1	0.43
Forties	UK	40.3	0.34
Ekofisk	Norway	43.4	0.14
Statfjord	Norway	38.4	0.27
Oseberg	Norway	33.7	0.31
Flotta	UK	35.7	1.14
Fulmar	UK	39.3	0.26
Gullfaks	Norway	28.6	0.44
Maureen	UK	35.8	0.55
Source: Horsnell & Mabro, 1993, Oil Market and Prices, p246			

Table 2.1:Major North Sea Spot Traded Crudes

ership has reinforced the Brent crude as a genuine international crude. It also helps to reduce the possibility of market squeezes and ensures the competitive price discovery process.

Other North Sea oil: apart from Brent Blend, other UK sector crudes include Forties, Flotta, Fulmar and Maureen. In the Norwegian sector production is made up of four main grades: Oseberg, Ekofisk, Statfjord and Gullfaks. Table2.1 shows the gravities and sulphur content of the main traded grades of North Sea crude.

As well as various markets for Brent blend, there is an active trade in other grades of crude oil as listed above. In most cases there are purely wet markets, in other words, spot trade, usually conducted within a month of the loading date of the oil, or occasionally the resale on a delivered basis of cargoes that have already been loaded.

Given various qualities of crudes in the area, the North Sea spot markets are almost totally reliant on the Brent market to fulfil their pricing function. Spot North Sea trades are agreed as a differential against Brent Blend price.

The USA

The USA is the largest crude oil market in the world. It had a production of 7.74 mb/d in 2000 and its daily oil demand was 18.74 mb/d. The short fall was covered by imports of 11 mb/d - over 25% of total world oil trade. The majority of import crudes come from Venezuela, Saudi Arabia, Canada, Nigeria and Mexico. Some of these imports are priced against Brent Blend while others are priced against WTI. West Africa and the Mediterranean spot trades are priced using the Brent price as a benchmark. Middle East spot crudes are priced as differentials against Dubai which is subsequently priced against Brent. Spot trades from Latin America are primarily priced as differentials against WTI. Since substantial amounts of imports for the US come from the Middle East and South America, the Brent and the WTI prices are linked through the physical spot trades among the imported crudes.

Unlike Brent, US domestic crude is largely traded domestically, with only negligible quantity traded internationally. The majority of spot trades consists of West Texas Intermediate, Alaska North Slope, West Texas Sour, and Light Louisiana Sweet.

West Texas Intermediate (WTI): The most important crude in the US is West Texas Intermediate (WTI). Like Brent, it is a blend of several crudes. The WTI par grade is 40° API and has 0.4% sulphur content, which is slightly lighter and sweeter than Brent. Its delivery point is Cushing, Oklahoma, the nexus of spot market trading in the United States. Parcels are usually 50,000 to 100,000 bbls. Production of WTI amounts to about 1 mb/d. The market for WTI and the price relationship in the US are driven by pipeline logistics. The importance of WTI is its nexus position in the pipeline logistics that it can meet the demand both towards Midwest and Gulf Coast. As a result WTI not only is the marker crude in domestic crudes trade, but it also has a strong influence on internationally traded crude oils.

West Africa

The largest producers in the region are Nigeria, Angola, Gabon, Congo, Equatorial Guinea and Cameroon. In 2000 3.29 mb/d of the production was available for export. Of them 1.4 mb/d of the production were exported to the USA. The bulk of the remainder goes to Europe, with minor quantities moving into Far Eastern markets.

While the majority of exports move under term contracts, a substantial volume is spot traded. Although more than 50% of exports reach US Gulf Coast, West African trade primarily uses Brent Blend as a benchmark. Thus it is not unusual for a trader to match up a spot sale f.o.b. West Africa priced against dated Brent with a trade with a US refiner who wishes to buy c.i.f. Gulf Coast on WTI related price. Hence West Africa spot trades generate a source of arbitrage between Brent and WTI markets which is effectively a physical linkage of the two.

The Mediterranean

Production in the Mediterranean was about 4.5 mb/d in 2000. The largest producers are Algeria, Libya, Egypt and Syria. The spot market consists of production by countries in the area together with volumes sold c.i.f. in the region by the Russians and the

Iranians. The major crude for spot trade from the Mediterranean producing nation is light sweet Algerian and Libyan grades. Year 2000 production in Algeria and Lybia was about 1.47 and 1.58 mb/d respectively. The trade in Libyan oil is very much affected by the US sanctions on trade with Libya imposed in 1986. Once again spot trade in the Mediterranean tends to be priced as a differential to dated Brent.

The Middle East Gulf

82% of the 23 mb/d production in the region is exported. Of these 2.5 mb/d are transported to the US. The prices paid in the Gulf spot markets are related to the three sets of Official Selling Prices (OSP) in Oman, Qatar and Abu Dhabi. All three countries OSPs are announced retroactively, and apply to all cargoes loaded in the previous month. These OSPs are calculated using Dubai prices over each calendar month as a base with an added premium in each month. The characteristics of Dubai prices feed all term sales priced off Dubai (i.e. Saudi, Iranian, Kuwaiti, exports) those with reference price to OSPs (i.e. Abu Dhabi, Oman, and Qatar), and all Gulf spot trade. Since the Dubai price is derived as a differential to Brent market, OSPs in the Gulf are essentially driven by western factors with one month's lag. Effectively the Middle East Gulf is priced with reference to Brent market.

The Far East

Apart from being a large importer of crude oil from the Middle East, the Far East also trade grades of crude oil indigenous to the region. They region's largest producers are

China (3.2mb/d), Indonesia (1.4 mb/d), Australia (0.8mb/d) and Malaysia (0.8mb/d). Spot trade is concentrated on Indonesian and Malaysian grades. Prices are traded against Asian Petroleum Price Index (APPI) and Indonesian Crude Price (ICP) on a weekly basis.

World oil forward markets

A forward oil contract is a tailor-made deal, specifying price, quality, and delivery date in the future between a buyer and a seller. The three largest forward markets are for Brent, Dubai and WTI.

Brent, Dubai and WTI.

Brent 15 day market

The Brent forward market is also termed '15 day' market. This specific term comes from the 15 day notice of nomination for delivery of a forward contract given by the seller to the buyer. The nomination is for a specific cargo lot and can be passed to another buyer. This process of passing nominations can continue until 5pm GMT on the last day on which the notice can be validly served, given the nominated 3-day loading window. Once the cargo is 5-o'clocked, it becomes a dated Brent-spot cargo. The most important characteristic of the forward markets is that the number of forward contracts far exceeds the number of physical contracts available each month. A large number of contracts are "booked out" before the nomination process takes place.

Dubai Market

The biggest difference between Dubai and Brent markets is the nomination procedure. Dubai forward market does not have the equivalent of Brent's 15-day nomination system where the seller has the choice of loading range. In Dubai market the initial choice of loading date is at the buyer's discretion. The buyer's nomination is accepted in the majority of cases. However if the seller rejects it, they must submit a three-day loading range back to the buyer together with the rejection.

WTI Market

The forward market for WTI is effectively EFPs (exchanges for physicals). An EFP is a flexible means of delivery agreed between two participants of NYMEX. It could transfer any grade of crude oil at any location in the world.

Interlink among Brent, Dubai and WTI

Price formation among the three forward markets is very much based on price differentials. Dubai prices are derived by price assessment agencies from market talk of, and trading in, the Brent-Dubai Fateh differential. Dubai is also very occasionally traded against WTI.

The relationship between the spot and the forward markets

A special feature of the oil markets is their dependence on the infrastructure of the delivery process. Loading schedules at terminals and pipeline schedules are normally settled well in advance, together with the chartering of tankers, with little change in the supply of oil in the short term. The price discovery process, therefore, also takes place well in advance in the forward and futures markets. In reality, spot trades are priced as differential to forward prices.

Unlike organized futures markets, spot and forward deals are carried out via telephone, fax and other means of communication. Bilateral / multilateral trades are executed by brokers, traders, and other interested participants. There is no centralized organization collecting information on the deals, reporting deals on screens at the exact time, exact place or providing security by acting as counterparts of each deal in a clearing system. These characteristics reflect the fact that spot and forward markets are very much informal markets. The tasks of price assessment and reporting of spot and forward prices are that of the price reporting agencies that will be discussed at a later section.

World oil futures markets

A futures contract is an exchange traded standardized contract with a pre-determined future expiry date, quality and delivery place and time, allowing market participants to concentrate on price determination only. The two largest crude oil futures markets by volume are the International Petroleum Exchange (IPE) and the New York Mercantile Exchange (NYMEX) where the Brent futures contract and the Light Sweet Crude No.2 contract are traded, respectively. Brent Blend is the underlying physical for the IPE futures contract while WTI is the underlying physical for the NYMEX contract.

The Brent futures contract

The Brent futures contract is quoted in US dollars. The trading unit is set at 1,000 barrels per contract. The Brent contract was launched, in its current form, in June 1988. Its underlying physical base is pipeline-exported Brent Blend, which is supplied at the Sullom Voe terminal in the North Sea. Minimum price fluctuation is one cent per barrel, equivalent to a tick value of $10. Trading hours are from 10:03 A.M. to 20:13 P.M. (London Time). Contracts are open for twelve consecutive months, then quarterly out to a maximum twenty-four months and then half yearly out to a maximum thirty-six months.

Participants in Brent market include not only the oil producing companies, but also downstream refiners, traders and finance houses such as investment banks, fund managers, etc.

The International Petroleum Exchange (IPE) is a formal, open-out-cry futures exchange. Brent crude futures are traded on the IPE and cleared by the London Clearing House. Trading ceases at the close of business on the business day immediately preceding the 15th day prior to the first day of the delivery month, if that is a banking day in London. If the 15th day is a non-banking day in London (including Saturday), trading ceases on the business day immediately preceding the first business day prior to the 15th day. The underlying of the futures contract is the Brent forward contract described previously.

Brent Crude Mutual Offset Agreement

The Singapore International Monetary Exchange (SIMEX) provides a facility to trade and clear Brent Crude futures under a Mutual Offset Agreement with the IPE. This allows positions opened in either IPE or SIMEX to be cleared and offset in either London or Singapore.

The WTI futures contract

NYMEX's light sweet crude was introduced in 1982. Trading unit is set at 1,000 barrels per contract. Trading hours are from 9:45 A.M. to 3:10 P.M. (New York time) for the open outcry session. Trading months are available for 30 consecutive months plus long-dated futures initially listed 36, 48, 60, 72, and 84 months prior to delivery. Price Quotation in US dollars. Minimum Price Fluctuation in 1¢ per barrel, ($10 per contract).

Delivery is located at free-on-board (*f.o.b.*) seller's facility, Cushing, Oklahoma, at any pipeline or storage facility with pipeline access to Arco, Cushing storage, or Texaco Trading and Transportation Inc. All deliveries are rateable over the course of the month and must be initiated on or after the first calendar day and completed by the last calendar day of the delivery month.

Accepted crudes for delivery consist of six domestic grades and six foreign grades.

These specific domestic crudes have the sulphur content of equal or less than 0.42%, as well as no less than 37° API nor more than 42°API gravity. The six domestic grades are: West Texas Intermediate, Low Sweet Mix, New Mexican Sweet, North Texas Sweet, Oklahoma Sweet, South Texas Sweet.

The foreign crudes are Brent Blend (UK), Oseberg Blend (Norwegian), Forties Blend (UK), Bonny Light (Nigerian), Cusiana (Columbian), and Qua Iboe (Nigerian). The sellers of foreign grades receive a premium and discount according to the contents of the physical crude. While sellers of Brent Blend, Oseberg Blend and Forties receive a discount, buyers of Bonny Light and Cusiana receive a premium. Qua Iboe will have no differential for delivery.

Expiry dates of the contracts are the third business day before the 25th of the prior month. On the 25th, pipeline companies begin to schedule the next month's shipping program.

The relationship between the forward and the futures markets

The most distinctive difference between forward contract and futures contract is that former is an informal market with participants only from oil industry while the latter is an organized formal market with participants both from oil and non-oil industries. As a result volume of futures markets are much larger than forward markets. Futures prices are far more transparent and widely available than forward. 99% of futures contracts are closed out before expiry. From a price discovery process point of view futures markets play a dominant role although spot and forward prices are inseparable integral parts.

2.2.1 Brief history of oil price determination

The market related formula pricing is a method for defining the sale price of one export crude by relating it to another crude taken as a reference. It was adopted by Mexico as an alternative to netback pricing in 1986 and has since become a widely accepted pricing method.

Before 1973 oil prices were strongly influenced by seven major oil companies. Prices then could be described as low and stable. From 1973 to 1986 OPEC was the major power weighing on the world oil price. Oil prices were determined around the so called "OPEC administration pricing formula". A price set at the meeting of OPEC oil ministers was used as a reference by oil-exporting countries. Using Arabian light as their reference crude, OPEC members fixed their official selling prices for their own crude varieties. This pricing formula lasted for 12 years during which the world witnessed two oil shocks in 1973-1974 and 1979-1980. The administration pricing formula was terminated in 1986. It was abandoned because the burden of holding the OPEC official line became unbearable for Saudi Arabia. Saudi Arabia had been acting as the 'swing' producer and reducing its production to accommodate quota violations by other member countries in order to maintain the OPEC administered price. The relentless cut of production by more than 50% which translated to substantial loss of revenue finally led to the scrapping of the administration price.

Some structural changes in the oil industry took place during the period of 1973 to 1986: (a) higher oil prices made further exploration and production viable. There were increases in non-OPEC oil production in the former Soviet Union, the North Sea, Alaska, Mexico, West Africa and Oman; (b) two recessions and the subsequent economic downturn in the industrialized nations reduced the demand for oil; (c) high oil prices induced energy conservation and interfuel substitution practices against oil were also widely adopted. The above changes contributed to the reduction in demand for OPEC oil. When demand fell many OPEC member countries tried to increase their market share so that their oil revenue could be kept intact. Since no member countries wished to curtail their production and take reduced revenue anarchy appeared within OPEC which eventually brought down oil prices largely orchestrated by OPEC.

What has replaced OPEC administered prices is the market-related formula which takes into account changes both in demand and supply. The structural changes listed above not only reduced the dominant position of OPEC in price setting by increasing the choice of oil supplies for the consumers (OPEC v. non-OPEC) but also increased flexibility of consumers' choice for alternative sources of energy (oil, coal and gas). These changes add to the volatility of oil prices in the short run although they help stabilize oil prices in the long run. The trading markets are there to accommodate the changing quantity of demand and supply and carry out the price discovery task.

2.2.2 Oil price reporting system

There are two types of price reporting agencies: first one concentrates on physical trades, second one concentrates on screen services. In this section the price reporting roles and pricing process of these two groups are briefly discussed.

Physical trades reporting agencies

Major oil price reporting agencies in this group include Platt's, Petroleum Argus and London Oil Reports (LOR). These agencies produce hard copy price assessment which then become the base for contractual price which is known as the differential price to spot price. As seen from section 2.2 Brent crude and WTI are the two most widely used spot prices for differential pricing. In other words they are the two most important marker crudes in the world.

1) Platt's

Platt's price are the most widely used in the oil industry and also the first agency which established itself in the field. In crude oil price reporting it lags behind Petroleum Argus, its first oil price reporting was in 1983. It now runs price reporting in offices in New York, California, Houston, London, Singapore and Tokyo. Platt's produces a daily price report, Platt's Oilgram covers world crude oil and product price, US domestic product prices as well as a daily and a weekly newsletter.

2) Petroleum Argus

Petroleum Argus grew out of Europ-Oil Prices, initially focused on European oil product prices, before covering worldwide crude oil and product price reporting. It was the first service to make daily assessments of crude oil markets in 1979. Petroleum Argus now has offices in London, Houston, Singapore and Tokyo, producing on a daily bases, a crude oil market report, four regional product price reports; on a weekly basis, newsletter and market reports; on a monthly basis, a data collation report.

3) London Oil Reports

London Oil Reports was founded in late 1970s, initially as a weekly newsletter with some price assessment, later moved into oil market and price reporting. It started to report oil and petrochemical prices after the 1985 merger with Independent Information Services, an agency has assessed petrochemical prices. Oil reporting is conducted in London, Houston and Tokyo.

Spot price reporting

Currently the price assessment agencies use a "time stamped" bid-offer range of a standardized cargo methodology. This means the oil price is denoted by a bid-offer range of a standardized commodity for each crude oil type. eg. In most widely quoted Platt's specification, dated Brent is assessed as the price of 500,000 barrel cargo of Brent due to load at Sullom Voe within 5-15 days of the assessment. The reporter needs to judge the prices on the basis of the deals done during the day, as well as on the basis of the talk within the market at the time stamp. In a thinly traded market, market talk, ie. asking market participants and brokers at which price levels they would negotiate, prevents the price assessment being too heavily influenced by just a few of the deals. The price reporting is more of an art than science.

Although price reporting agencies try to produce daily absolute oil prices, most spot traded crude oils are not traded as absolute prices, but as differentials. Crude oils in North West Europe, the Mediterranean and West Africa all tend to be traded as a differential to published assessment to dated Brent. Dated Brent itself tends to be traded as the differential of published assessment of forward Brent. Likewise Latin America tends to trade spot crude in differential to WTI and WTI itself tends to be traded as the differential to forward WTI. Another differential source of pricing comes from the use of price generated by futures prices. Both forward price formation and futures price formation will be discussed below.

Forward price reporting

Using Brent forward as an example of forward price determination is explained in the following:

Brent forward price assessment is produced with the following procedure: 1) assess the price of Brent for the forward month in which there has been the most traded in outright prices. Using the bid-offer ranges from the market and to a lesser extent market talk to derive the absolute price of the Brent forward price. 2) the next step is to get the other Brent forward prices. They can be derived from the current market bid/offer ranges.

Brent spot prices using differential can now be inferred from these Brent forward prices. If the assessment time is during trading or immediately after the close of IPE, they can also run a check from what price EFPs are being talked at, i.e. the difference between IPE price and the forward Brent price for a comparable month.

Futures price reporting

Futures contract prices for WTI and Brent crude are determined by demand and supply forces on the respective trading floors. Both exchanges are continuous markets. Prices are immediately displayed on the screens of exchanges by exchange staff and transmitted to other users through screens of electronic vendors such as Reuters and Telerate.

Due to its transparency, accessibility and continuity, Brent and WTI futures markets are the most readily available oil price discovery market place in the world. However spot, forward and futures markets are inseparable integral parts of the world oil market place. They fullfil different needs of various economic agents and are interdependent to one another. In this thesis emphasis is put on the two leading futures markets and the linkage of the two.

Screen based services

The leaders of the screen based services are Telerate, Reuters, Bloomberg and Knight Ridder. Platt's also provides a screen service. They combine price information screens and deal reporting with a news services. The role of screen services in contractual pricing is limited as compared to the hard-copy based oil price reporting. However they play a major role in conveying news which moves the market. This role is particularly significant in geographically separated trading. With terminals provided by these screen based services, news and market information are readily available anytime anywhere in the world. Geographic distances no longer play a role in physical information transmission. Information transmission from one market to the other implies market leadership or some kind of new information revealing process from the transmitting market. It is this **latter information transmission** which this thesis is to investigate.

2.3 Crude oil futures markets: IPE and NYMEX

Brent and WTI crude oil futures contracts are introduced in section 2.2. In this section details of the two futures contracts are compared and the linkages of the two are presented.

2.3.1 Specification of the two marker crudes: Brent and WTI

Brent and WTI crude oil futures contracts have almost identical specifications in terms of trading unit, quoting currency and minimum-price fluctuation. Details are listed in Table 2.2. These features enable the statistical analysis of the two contracts feasible.

Volume of the two contracts are also calculated and listed in Table 2.3. IPE contracts have around half of the volume of NYMEX's.

	IPE crude oil futures	NYMEX crude oil futures
Trading Unit Trading currency Trading Hours	1,000 barrel (42,000 gallons) US$ 10:02am - 20:13pm (London time)	1,000 barrel (42,000 gallons) US$ 14:45am - 20:10pm (London time)
Min price fluctuation	$.01 (1cent) per barrel ($10 per contract)	$.01 (1cent) per barrel ($10 per contract)
Max price fluctuation	no limit	$15.00 per barrel ($15,000 per contract) in two stages for 1st two contract months.
Daily margin	all open contracts are marked-to-market	all open contracts are marked-to-market

Table 2.2:IPE and NYMEX Crude Oil Futures Specification

	IPE daily average (000')	NYMEX daily average (000')
1995	56.8	110.0
1996	44.2	91.6
1997	41.9	97.0
1998	55.3	121.3
1999	64.5	147.1
2000	69.1	143.9

Table 2.3:IPE and NYMEX Crude Oil Futures Daily Average Volume

2.3.2 Linkage of the two marker crudes

While Brent market accounts for less than 5% of the world total trade, its effects by acting as a marker crude enables it to "control" 75% of the world trade. Meanwhile, the USA is the largest oil importing nation. Its domestic marker crude - WTI dominates the spot trade among both domestic and imported trades. Potential arbitrage opportunities exist when exported crudes to the US are priced as differentials against Brent.

Physical linkages between Brent and WTI

There are also two physical linkages between Brent and WTI. First is the physical delivery of the Brent crude against WTI futures contract, as Brent is one of the three foreign crudes that is deliverable against WTI futures contracts. The second is the exchange of (WTI) futures for physical (Brent). This feature provides a special linkage between WTI and Brent. When this function is exercised, WTI futures position is closed out, a Brent cargo is taken for delivery. Although Brent futures contracts offer EFP facilities they are limited to Brent Blend only.

Trading link between Brent and WTI with no arbitrage conditions

Given the easy access to WTI and Brent futures markets the linkage of the two markets is further enhanced by the arbitrage trading by market participants. WTI-Brent spread is a regularly traded one. The presence of financial institutions in addition to oil users adds liquidity to the markets. At IPE about 64,000 Brent contracts were traded in 1999 compared to 151,000 WTI contracts per day in New York . Real time prices are available through screen services vendors. Eg. Reuter-2000 system transmits real-time WTI and Brent Blend futures prices at its terminal all over the world. As a result, trade details and information embodied within are disseminated through the terminals all over the world. Any arbitrage opportunities can be seized immediately and linkages of the two markets are further strengthened.

2.4 Conclusion

This chapter establishes the pricing role that IPE and NYMEX play in the world oil market and establishes the close link between the two. Therefore it is interesting to look at the relationship between these two markets, and indeed to uncover the market leader of the two. The focus of this thesis is the short term lead-lag relationship of the two energy futures markets. The implication of the results has a significant role to play in trading, hedging, speculation and regulation. Chapter 3 reviews the existing literature on the estimation of lead-lag relationship; the rest of the chapters investigate the empirical evidence of the information transmission mechanism between the two markets.

Chapter 3
Review of lead-lag relationships

3.1 Introduction

Does one futures market lead the other? This is an important question to all market participants. If, for example, NYMEX is found incorporating information significantly faster than IPE, then traders can profit by simply watching the NYMEX price changes and making deals with IPE price before the price movement takes place in IPE.

This chapter reviews methodologies on lead-lag relationships in the existing literature and how these methodologies can be used to examine relationships between NYMEX and IPE. The general outline for this chapter is as follows: Section 3.2 reviews the general framework upon which lead-lag tests are based. Section 3.3 introduces the concept of Granger Causality and its operational tests. Section 3.4 discusses factors that may affect the lead-lag relationship and their relevance to this thesis. Section 3.5 concludes and suggests further empirical analysis in the thesis.

3.2 General setting on Lead-lag relationship

Tests on lead-lag relationships in empirical work so far can generally be divided into two categories: correlation analysis and regression analysis. Each methodology is discussed below.

3.2.1 Correlation analysis

Correlation is one of the basic statistical tools a researcher can apply for data analysis. The correlation coefficient value varies between 0 and 1 with 1 indicating perfect correlation and 0 indicating no correlation. While auto-correlation examines the correlation between the current and past behaviour of the same series, the cross-autocorrelation focuses on the current and past behaviour of two different series.

Autocorrelation

$$\rho(k) = \frac{cov(y_t,\ y_{t-k})}{var(y)}$$

where k is the number of lags between y and its past value.

Cross autocorrelation

$$\rho_{xy}(i) = \frac{cov(x_t,\ y_{t-i})}{\sqrt{var(x)}\sqrt{var(y)}}$$

where i is the number of lags between x and past value of y.

The usefulness of autocorrelation and cross-autocorrelation lies in its predictability. High autocorrelation indicates predictability from the past information of the same market and high cross-autocorrelation indicates predictability from another market. This predictability is useful for detecting the lead-lag relationship since it can be interpreted as the existence of the market leader. For example, in the case of high cross-autocorrelation, if the return series of market X and the one period lagged return series of market Y have high correlation, then what happens today in market Y would have a strong effect on what would happen tomorrow in market X; thus market Y has predictability in relation to market X. In other words, market Y leads market X.

This methodology is crude but effective, as an indicator, and is often used in pre-modelling data analysis. For example Lo and MacKinlay(1990) in their search for causes of market overreaction use cross-autocovariance, an alternative of cross autocorrelation, of the returns of stocks as a lead-lag indicator and find the returns of large stocks lead those of smaller stocks.

3.2.2 Return analysis in a regression framework

(1) Univariate analysis

Another methodology widely used in empirical work to detect a lead-lag relationship in a bivariate framework is by adding leading and lagging variables in a regression and testing for the significance of the coefficients. This method is first proposed by Sims (1972) to test for the causality between money and income variables in macroeconomics. Later it is applied to financial futures markets by Stoll and Whaley (1990) through the examination of the relationship between Major Market Index (MMI) futures, S&P500 futures and their respective underlying stock indices. Chan (1992) extends the work on the lead-lag relationship through the effects of the release of macroeconomic news.

The theoretical model behind this methodology is encapsulated in Equation 3.1.

$$R_{A,t} = \alpha + \sum_{k=-n}^{n} \beta_k R_{B,t+k} + \epsilon_t \tag{3.1}$$

where $R_{A,t}$ is the return of asset A at time t, $R_{B,t}$ is the return of asset B at time t; k is the number of time periods that are used to test the length of leads and lags. There are n leads and n lags being tested in this equation. The coefficients with positive subscripts $\beta_1, ...\beta_n$ are lead coefficients and those with negative subscripts $\beta_{-1}, ...\beta_{-n}$ are lag coefficients. If lead coefficients are significant then A leads B, meaning A has predictive power over B. If lag coefficients are significant then A lags behind B, meaning that B has predictive power over A.

Works that have adopted this methodology include: Frino et al (2000) in the investigation of SPI - Australia stock index futures and its underlying equities around the release of macroeconomic news and specific stock news; Grünbichler et al (1994) in the analysis of the effects of the introduction of screen trading on the relationship between DAX futures and the underlying index; Chiang and Fong's (2001) on the Hong Kong stock index and index futures.

The advantage of this methodology lies in its simplicity of application, in particular when detecting the direction of information transmission. All the above mentioned papers use intra-day data. Lead-lag relationships are examined in the interval of an hour, 30mins, 5 mins, etc. Like other time series analysis, this methodology may suffer from the plague of serial correlation and heteroskedasticity. Generalized Method of Moments (GMM) and White's (1982) method are often used to find consistent estimation of parameters to correct this problem. Another more serious problem inherent in this methodology is that it lacks relevant statistical properties to be used as a rigorous statistical test. It may suffer from instability due to different lag length in the regression.

However, the advantage of this univariate lead-lag method, is that it is particularly useful for intra-day lead-lag analysis and it is applied to the lead-lag relationship between IPE and NYMEX in the simultaneous trading session in 5-minnute intervals in this thesis.

(2) Multivariate analysis

The return analysis for a lead-lag relationship can also be applied in a multivariate framework. Brennan et al (1993) and Chordia and Swaminathan (2000) use the following bivariate vector autoregression system:

$$r_{A,t} = \alpha_0 + \sum_{k=1}^{K} \alpha_k r_{A,t-k} + \sum_{k=1}^{K} b_k r_{B,t-k} + u_t \tag{3.2}$$

$$r_{B,t} = c_0 + \sum_{k=1}^{K} c_k r_{A,t-k} + \sum_{k=1}^{K} d_k r_{B,t-k} + v_t \tag{3.3}$$

If the ability of lagged returns of B to predict current returns of A is better than the ability of lagged returns of A to predict current returns of B, then B leads A. Empirically it is achieved by testing whether $\sum_{k=1}^{K} b_k$ is greater than $\sum_{k=1}^{K} c_k$.

This methodology serves well as a lead-lag directional test. However it lacks relevant statistical properties to be used as a statistical test. In fact this is the general comment on all methods reviewed in this section. Furthermore, there exists a need for a theoretical definition of lead-lag relationship. Since the lead-lag relationship is about prediction of one event/series to the other, in this sense the concept of Granger Causality can be utilized. As will be explained in the next section, some of the above mentioned tests can be regarded as empirical applications of Granger Causality.

3.3 Granger causality

3.3.1 Definition of Granger causality

The definition of Causality is first introduced in Granger's 1969 paper and further discussed in Granger's 1980 paper. It is often referred to as Granger Causality. "A series y_t is said to cause x_{t+1} if it contains information about the forecast ability for x_{t+1} that is contained nowhere else in some large information set, which includes x_{t-j}, $j \geq 0$ " (Granger & Lin, 1995). Predictability of variable Y to variable X means currently available Y is informative towards future value of X.

It is worth noting that Granger causality is a concept of predictability rather than an actual causal relationship, although in certain circumstances the actual causal relationship does exist. It is useful for testing hypotheses about the predictability of a series. Acceptance (or rejection) of Granger causality of Y in relation to X means the Y series has (or has not) predictability over the X series. This predictability can be used to test the lead-lag relationship: if Y series does not Granger cause X series,

Y market does not lead X market. Conversely if X series does not Granger cause Y series, then X does not lead Y. Granger causality is often used in empirical work to detect any possible lead-lag relationships. To make the causality concept operational various tests are proposed in the literature as will be shown below.

3.3.2 Applied Granger causality

The return analysis for detecting the lead-lag relationship in Equations 3.1, 3.2 and 3.3 can be regarded as simple applications of Granger Causality in the univariate and multivariate time series analysis. The application lies on the predictability of one event to the other. It is worth mentioning some shortcomings of the causality test. Granger Causality is an indicator, not a statistical test. This indicator is built in a model to make it operational. This is why there are many procedures to test the causality. Below we briefly mention some new operational applications of Granger Causality which appear in recent work to give a general flavor of the application.

Granger causality in multivariate analysis

One such example is Hsio's (1981) linear causality test which combines Akaike's final predictive error criterion (FPE) and the definition of Granger causality in a framework of bivariate stationary VAR representation. Moosa and Silvapulle(2000) apply this test in the framework of an Error Correction Model (ECM).

Another development in the Granger analysis in VAR is the inclusion of co-integrated variables. Granger (1988) explains that with the existence of co-integration, there must be causality in at least one direction. Using this framework Schwarz and

Szakmary (1994) examine the relationship between NYMEX traded crude oil and crude oil futures contracts on a daily basis. Their results suggest futures dominate in price discovery process, which are in direct contrast to Quan's (1992) result with monthly data that cash leads futures.

Granger causality in variance and higher moment analysis

Under the defined concept of causality, development on the lead-lag relationship has so far been on the functional form and underlying data generating process. One extension is the causality in variance that is introduced by Cheung and Ng (1996). It can be viewed as an extension of the Wiener-Granger causality in mean (Granger, Robins and Engle, 1986).

Granger causality in non-linear analysis

Furthermore a non-linear causality test, is proposed by Baek and Brock (1992) and is applied in the studies of price-volume relationship in the crude oil futures markets by Moosa and Silvapulle (2000), and Hiemstra and Jones (1994). Another example using non-linear Granger Causality is that by Okunve et al (2000) on real estate and stock markets.

Granger causality in High Frequency analysis

Finally, the availability of high frequency data and computation power enable the lead-lag relationship to be analyzed within a day. Stoll and Whaley (1990), and Chan (1992) study the returns of Major Market Index futures, S&P500 futures and the returns of their underlying indices in 5-minute intervals. Abhyankar (1995) studies the

FTSE100 cash and futures markets using time intervals of 1 hour. Grünbichler et al (1994) investigate the effects of screen trading on the relationship between DAX futures and the underlying cash markets using 5-minute returns. All the above mentioned work indicates the lead of futures markets over underlying cash markets. Possible reasons are discussed in the next section. The usefulness of the high frequency Granger Causality test comes from the fact that it can be easily applied in empirical work. For this reason this methodology will be applied to the lead-lag relationships between IPE and NYMEX during simultaneous trading hours in Chapter 6.

In the following section we are going to review the factors that may affect the lead-lag relationship in the short run and discuss those that may affect the relationship between IPE and NYMEX.

3.4 Factors that may affect lead-lag relationship

The reasons for a market lead-lag relationship have been investigated from several routes by different investigators. Here we categorize them briefly into 5 groups, each of which will be discussed below.

3.4.1 Market friction and regulation

Market frictions which are not taken into account in theories of finance may have a large impact in empirical lead-lag relationship analysis. Stoll and Whaley (1990) demonstrate that relatively low trading costs may help create a market leader. Other market frictions such as capital requirement, or short-selling restrictions may affect the market lead. Details of contract execution fees, capital requirements for exchange members and brokers, and cost of exchange membership all have a role to play in relation to the operation of the market. Discussion along this line for IPE and NYMEX maybe interesting but beyond the scope of this thesis.

3.4.2 Non-synchronized trading and the frequency of trading

Lo and MacKinlay (1990) investigate non-synchronized trading effects on the lead-lag relationship through cross-autocorrelation analysis on futures and find futures markets dominate those component stocks that have high probability of non-trading. Stale quotes, which may cause the lead of futures to cash is examined by Shyy et al (1996). The authors demonstrate that index futures returns appear to lead index returns when index and futures transaction prices are used in the calculation of returns, but that the reverse occurs when returns are calculated using stock and futures quotes. The prohibition of short selling in stock markets slows the information incorporation into cash prices while the futures market has no such asymmetric price change ruling. Lower trading activity implies that the securities are less frequently traded, so that observed prices lag "true" values.

Non-synchronized trading due to the discrepencies in the frequency of trading is not a serious problem for the analysis of IPE and NYMEX when both exchanges are open, as it is in the analysis of stock index and its underlying component stocks. However, related to the frequency of trading, is the concept of volume - the number of contracts being transacted - which is also connected to the concept of liquidity. Both volume and volatility are important variables in market microstructure analysis which will be discussed in more detail in Chapters 6 and 7.

3.4.3 Immediacy of trading

In addition to the above, Grossman and Miller (1988) and Miller (1990) show that futures markets may provide more immediacy to traders than does the spot market. What follows is that if a trader has private information and he/she needs to act speedily, he/she would choose futures market to transact.

This factor does have much relevance for our two crude oil futures markets in relation to their usage for hedging, speculation and trading, as both markets offer such immediacy. However, there is the issue of convenience of delivery location when contracts are carried to expiry. This case is rare - less than 1% of futures contracts are kept open at expiry and they are not the subject of investigation in this thesis. Furthermore, there is the issue of the two markets' opening at different times and the issue of availability of screen trading outside floor trading hours, which may affect the immediacy of trading. These issues will be discussed in Chapters 4 and 5 in relation to spillover effects from between NYMEX to IPE.

3.4.4 Intensity of trading and adverse information selection problem

Information dissemination may be affected by the intensity of trading activity which may affect the lead-lag relationship. One important reason for trading is the existence of asymmetric information. Bagehot (1971) introduced the basic information asymmetric model with heterogeneously informed traders: the **specialists** (market makers), who have no private information; **uninformed traders** (liquidity traders), who, like market makers, have no private information either; and finally **informed traders**, who have private information. The existence of informed traders imposes an "information cost" to the market. When market makers trade with informed traders, they always lose. To remain solvent, they must offset these losses by making gains from uninformed traders. These gains arise from the bid-ask spread. Consequently, liquidity traders always lose to informed traders. These adverse selection costs faced by discretionary liquidity traders may be reduced by trading in futures markets as discussed in work by Subrahmanyam (1991) and Chan (1992). Admati and Pfleiderer (1988) show that, "in general, trades of both discretionary liquidity traders and informed traders cluster, with each group preferring to trade when the market is thick."

Chapter 7 is specifically devoted to the modelling of trading duration which will look at the intra-day trading duration patterns of IPE. Due to the lack of quality tick by tick trade data for NYMEX futures contracts[2] analysis is conducted on IPE only.

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2 Tick-by-tick transaction data for IPE crude oil futures are available by unit of a second; high frequency data for NYMEX crude oil futures are only available by unit of a minute. Direct comparison using two data sets is difficult.

3.4.5 Sources of public and private information

Kyle (1984) classifies information into two sources: private and public. Public information is observed by all market participants, whereas private information is only observed by the informed traders.

Possession of private information may produce the market leader. In index futures and cash market analysis, possession of private information on specific firms would make sense to trade specific stocks rather than the whole futures index, which may be the reason for the cash to lead futures. Subrahmanyam (1991) and Chan (1992) show that if an informed trader processes firm-specific information, it may be optimal to trade shares of individual firms directly.

Where does private information come from? One source of information asymmetry comes from the unobservable cost and information structure. Although public information is widely available, the cost of acquiring detailed information and the cost of analyzing information exclude certain traders from becoming informed traders.

The analysis of publicly available information requires time and skills, yet could reveal surprising results. For example, the study by Christie and Schultz (1994) on the quotes given by NASDAQ dealers uncovers the collusion of dealers who make unlawful profits by avoiding odd quotes. In fact, the study of market trading variables, such as quotes, trade volume, bid-offer spread have been the fast developing subject of market microstructure, which will be explained in more detail in Chapter 7.

Another source of private information is insider information, which is targeted by all regulators.

A related issue to the source of information is that of information transmission channels. Price is a widely accepted information transmission vehicle. Other traded related variables are gaining more and more attention as information transmission vehicles. For example, volume, volatility and bid-offer spread reflect market conditions as well as the behaviour of market participants (Hasbrouck 1991). In this spirit, tick-by-tick transaction data are analyzed in Chapter 7, to uncover the market conditions and the effects of NYMEX trading on IPE. This methodology is applied for the first time in energy futures markets.

3.5 Conclusion

This chapter reviews the main methodologies used in empirical examinations of lead-lag relationships. These methodologies are useful in practice but are crude in statistical robustness. Possible causes of the existence of the leading market are discussed. An empirical investigation of the lead-lag relationship between IPE and NYMEX will be carried out in Chapter 6. A transaction-by-transaction analysis of IPE trading will be carried out in Chapter 7 to uncover the direction of information transmission between IPE and NYMEX.

Chapter 4
Univariate Analysis

4.1 Introduction

After theoretical physical and trading linkages between IPE and NYMEX are established in Chapter 2, the empirical information transmission mechanism between NYMEX and IPE crude oil contracts becomes the research target of this chapter and the next two chapters. Together they address the concomitant questions of: how fast information is transmitted (e.g. within the same day or overnight); in which direction the information flows (whether there exists a market leader); and any characteristic differences between simultaneous trading and non-simultaneous trading. This chapter examines spillover effects between IPE and NYMEX using daily data under both overlapping and non-overlapping trading hours. It depicts general characteristics of the interaction between the two markets and points out directions for further investigation in the next two chapters.

Much of the research to date on futures markets has focused on the interaction between the cash and the futures tiers of the crude oil market. In contrast, this research question focuses on the information linkages between the two geographically separated markets. Variations of this question could be: Does the law of one price hold for the two markets? Is one market more efficient than the other in assimilating information? Does one market 'lead' the other in its pricing function?

Section 4.2 of this chapter starts with the literature review on energy futures markets and - more importantly - on the issue of information transmission between the two markets. Section 4.3 continues with a review of the data at our disposal, their characteristics and shortfalls (where inevitable), and the consequences in the choice of methodology. Section 4.4 discusses the methodology employed and the interpretation of empirical results and Section 5.5 concludes with a summary of the most important findings and suggestions for further research.

4.2 Literature review

We concentrate on the subject of information transmission between geographically separated markets where research has been restricted to the financial markets only, with work largely concentrated on stock markets. The dominance of the US market is well-documented. King et al (1990 & 1994) investigate the volatility spillover issue among stock markets and find evidence supporting contagion effects. Eun and Shim (1989) find that innovations in the US are rapidly transmitted to other markets, whereas no single foreign market can significantly explain US market movements. Koutmos & Booth (1995) find: (a) price interdependencies, with significant price spillovers from New York to Tokyo, as well as from Tokyo and New York to London; and (b) extensive price volatility interdependencies and sign effects.

Hamao et al (1990) examine the transmission mechanism in common stock prices across Tokyo, London and New York stock markets and suggest that there is some informational inefficiency in these markets. Susmel and Engle (1994) re-examine the evidence of spillovers in returns and return volatility between the US and UK but do not find strong evidence of international volatility spillovers, even for the period including the 1987 stock market crash. The high frequency data used in the latter paper may have played an important role in the different results of the two papers.

We focus on the informational linkage of the two well established energy futures markets in New York and London. In particular we investigate the spillover effects in the returns from NYMEX to next day IPE morning trading as well as information transmission effects in the returns from early morning IPE trading to NYMEX.

4.3 Data

As shown in Figure 4.2, NYMEX trading hours are from 9:45 EST (14:45GMT) to 15:10 EST (20:10GMT) while IPE trading hours are from 10:02 GMT to 20:13 GMT. Two different time phases are examined: (1) the non-simultaneous trading session when London is open and New York is closed, i.e. 10:02-14:45 GMT; and (2) the simultaneous trading session when both markets are open, i.e. 14:45-20:13 GMT. The market efficiency hypothesis implies no lead-lag relationship in phase 2. By separating the overlapping trading hours and non-overlapping trading hours, market dependencies due to non-trading hours are filtered out.

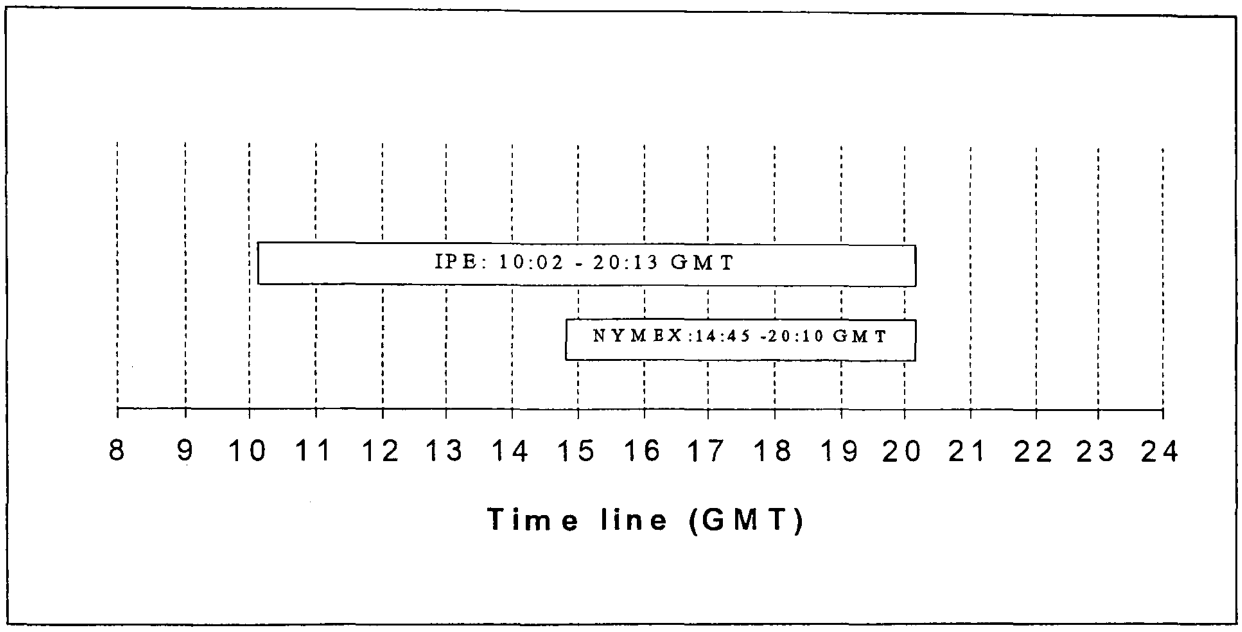

Figure 4.2: Opening - Closing Time of IPE and NYMEX

Returns of relevant trading sessions are calculated using the log returns on daily open and close data in the crude oil futures contracts. London data are obtained from IPE while New York open and close prices are reported by NYMEX and are available on Datastream. Data series are from 4th January 1994 to 30th June 1997.

To counter the non-synchronising problem due to different trading hours, the London open to close log return data series is divided into two: 'open to noon' return (IPEOT); and 'noon to close' return (IPETC). The noon data are extracted from the newly released IPE tick data 5 minutes before the opening of trading of NYMEX energy futures contracts. NYMEX opens at 9:45 EST (14:45 London time) Monday to Friday; its 'open to close' return series is denoted as NYOC. The average price of the last five minutes trades between 14:40 and 14:45 GMT is used as the London noon price. Trading data when one market is open while the other is closed due to holidays are discarded to maintain consistency. A dummy variable for Mondays and public holidays is constructed to capture any such effects.

The continuous futures series are constructed by using the nearest contract and switching to the second nearest contract when the former contract has 5 remaining working days before expiration. The reason for choosing the nearest contract is that it has the desirable characteristics of large volume and liquidity. The 5 working days' cut off point could be considered arbitrary; however there is eye-ball evidence that the last 5-day trading volume of the nearest expiry contract declines significantly. A second dummy is constructed at the cut off point of changing contracts to capture this possible contract-switch effect.

Although NYMEX ACCESS, the screen based global trading network launched in 1993, gives a constant window on market activity when the open out-cry trading is closed, its volume on average is less than 5% of the exchange trading volume. Its role in information assimilation, price setting and hedging is limited. Ulibarri (1998) investigates price and trading volume relations of the near term futures contracts and finds ACCESS variables are not informative in predicting NYMEX prices. In this thesis investigation is concentrated on the open-out-cry trading of the exchanges where markets are the largest and most liquid.

Table 4.4 lists summary statistics for the three log return series. All series are stationary. The sample means for the three series are not significantly different from zero. The measures for skewness and kurtosis are highly significant at the 5% level: IPE morning return series has negative skewness while NYOC returns and IPE afternoon returns have positive skewness. "Fat tail" features exist in all three return series. Please note skewness and kurtosis of IPE morning and IPE afternoon are significantly different from each other. They may caused by the opening of NYMEX for trading, which alters the trading charateristics of IPE. Further analyses on this issue are carried out in Chapter 7. Lagrange Multiplier (LM) tests for ARCH effects with lags are significant, indicating the existence of heteroskedasticity. To take into account the heteroskedasticity problem, ARCH/GARCH modelling is used.

Model	**IPEOT**	**IPETC**	**NYOC**
Mean	0.0002	-0.0001	0.0006
Variance	0.0000	0.0002	0.0002
Skewness	**-0.1749**	**0.2116**	**0.2394**
Kurtosis	**4.06**	**2.81**	**2.38**
ARCH(12) - LM test	**135.31**	**121.19**	**137.59**
Ljung-Box Q(20)	29.25	**35.87**	30.88
Ljung-Box $Q^2(20)$	**115.00**	**31.00**	**45.62**
	0 lag*	1 lag*	0 lag*
Augmented Dickey-Fuller	**-29**	**-19**	**-28**
Phillips-Perron	**-841**	**-841**	**-822**
Serial correlation			
Lag1	0.0169	0.0145	0.0382
Lag2	0.0160	0.0947	0.0636
Lag3	-0.0819	0.0062	-0.0360
Lag4	-0.0166	0.0517	0.0302
Lag5	0.0063	0.0546	0.0333
Lag10	-0.0347	0.0827	0.0583
Lag length is decided by AIC and BIC; Ljung-Box Q(20) and $Q^2(20)$: serial correlation test of lag 20th order on return series and return series squared. Note: bold numbers are statistically significant at 5%.			

Table 4.4:Descriptive Statistics

4.4 Methodology and empirical results

The aim of this chapter is to gather empirical evidence on the information transmission mechanism between IPE and NYMEX. More precisely, investigation is on to uncover whether there are any spillover effects between IPE morning returns and NYMEX returns of the previous day; and whether there is a market leader during the IPE afternoon trading session. Time series models are suited for these purposes. Univariate Generalized Autoregressive Conditional Heteroskedasticity type of models (GARCH) are applied in this chapter. Box-Jenkins methodology is applied to model the mean equation and GARCH is used to model the time-varying variance.

4.4.1 Univariate models

ARCH/GARCH model

In this chapter we follow the ARCH (Autoregressive Conditional Heteroscedasticity) model developed by Engle (1982), later generalised by Bollerslev (1986) and known as the GARCH model.

$$R_t = \alpha + \epsilon_t \tag{4.4}$$

where $\epsilon_t \sim N(0, h_t)$, h_t is the conditional variance of the residual.

$$h_t = c_0 + a_1 h_{t-1} + b_1 \epsilon_{t-1}^2 \tag{4.5}$$

"General to specific" methodology is applied to construct the autoregressive moving average (ARMA) model in individual return series. This method assumes we do not have any prior knowledge about the model so that we start from a general model with large parameters then narrow down to a specific one by filtering out insignificant parameters using variable restriction tests. The General model is set up with 5 lags and 5 moving average terms in the mean return equation. Zero restrictions are imposed on the parameter one by one with with likelihood ratio tests to filter out insignificant terms while maintaining no series correlation in the residuals.

After the specific model is found in the mean equation, ARCH/ GARCH order is selected on the criterion of which model has the best fit. The results are shown in Table 4.5. Two series, i.e. the IPE morning session return (IPEOT) series and the NYMEX trading return (NYOC) series follow a GARCH(1,1) process while the IPE afternoon session return (IPETC) series follows an AR(2)-GARCH(1,1) process. All three models are reasonably presented. There is no serious misspecification. Serial correlation on standardised residuals and squared standardised residuals is tested by Ljung-Box Q test with 20 lags and both show no significant serial correlation. The different characteristics in the data series of IPE morning section and afternoon section can be interpreted as the result of spillover effects that will be explained later.

Monday / holiday effects & contract-switching effects on the conditional mean & variances of futures returns

Two dummy variables are incorporated in the mean and variance equations of each series. The Monday and holiday dummy variable takes the value of "1" on days after weekends and holidays, and "0" otherwise. The contract-switching dummy variable

	IPEOT	**IPETC**	**NYOC**
Model Specification	GARCH(1,1)	AR|2|-GARCH(1,1)	GARCH(1,1)
Constant	0.0002 (1.2887)	-0.0001 (-0.2688)	0.0005 (0.8952)
AR(2)		**0.0874** (2.7706)	
GARCH equation			
Constant	**0.000001** (2.5590)	0.000001 (1.7313)	**0.000002** (2.2443)
H(1)	**0.9290** (58.1624)	**0.9648** (104.2544)	**0.9647** (3.3125)
$E(1)^2$	**0.0498** (4.5864)	**0.0298** (3.7495)	**0.0284** (95.9835)
LL	3194	3203	2368
SK	0.13	0.02	0.05
KU	5.35	1.96	4.74
LB-Q(20) on residual	19.44	22.72	28.47
LB-Q^2(20) on residual squared	31.75	8.69	6.87
LR test on IPETC for common structure with NYOC		**7.02**	
Abbreviations: LL: Log likelihood function value; SK: Skewness of the standardized residual; KU: Kurtosis of the standardized residual; LB-Q(20) / LB-Q^2(20): Ljung-Box serial correlation test on standardized residual mean and standardized residual mean squared respectively, with 15 lags. LR test: likelyhood ratio test.			
Note: Bold numbers are statistically significant, Numbers in brackets are t statistics.			

Table 4.5:Estimation of GARCH models

takes on "1" on every first day that the second nearest futures contract is adopted and "0" otherwise.

$$R_t = \alpha + \epsilon_t + dummies \tag{4.6}$$

where $\epsilon_t \sim N(0, h_t)$, h_t is the conditional variance of the residual.

$$h_t = c_0 + a_1 h_{t-1} + b_1 \epsilon_{t-1}^2 + dummies \tag{4.7}$$

There are well documented Monday and holiday effects in stock markets (see French (1980). However, this effect is not significant in this investigation. As displayed in Table 4.6 the mean and variance of the returns of energy futures markets are immune to such 'irregular' days with one exception, ie. Monday / holiday effects on the variance equation of NYMEX open-to-close trading section. It can be interpreted that the first day returns of NYMEX after trading halts due to holidays seem to be more volatile than otherwise. The contract switching dummies are not significant in all cases.

Spillover effects on the conditional mean and variance of futures returns in non-overlapping trading hours

Foreign market trading activities are incorporated to test whether they have any significant effects on domestic markets. IPE morning return and volatility are utilised to test the information transmission from IPE to NYMEX of the same day. NYMEX return and volatility are used as spillover variable for the IPE trading on the following day.

	IPEOT	**IPETC**	**NYOC**
Model specification	GARCH(1,1)	AR[2]-GARCH(1,1)	GARCH(1,1)
Constant	**0.0004**	-0.0002	0.0004
	(2.0601)	(0.3667)	(0.6710)
AR(2)		**0.0887**	
		(2.7552)	
Mon/Hol D	-0.0007	0.0008	0.0009
	(1.4533)	(0.7268)	(0.7637)
Contract D	-0.0009	-0.0021	0.0010
	(0.8180)	(0.8162)	(0.4263)
GARCH			
Constant	0.0000001	-0.000001	-0.000003
	(0.1968)	(0.3133)	(0.6960)
H(1)	**0.9264**	**0.966**	**0.9659**
	(50.5546)	(103.1524)	(110.0002)
$E(1)^2$	**0.0521**	**0.029**	**0.028**
	(4.0672)	(3.6145)	(3.6526)
Mon/Hol D	0.000004	0.000009	0.00004
	(1.0061)	(0.5258)	(1.8555)
Contract D	-0.000004	0.000005	**-0.0001**
	(0.8715)	(0.2213)	(2.8512)
LL	3197	3204	2372
SK	0.13	0.01	-0.01
KU	5.39	1.95	4.67
LB-Q(20)	18.77	22.72	29.77
LB-Q^2(20)	32.24	8.69	6.35

Abbreviations: LL: Log likelihood function value; SK: Skewness of the standardized residual; KU: Kurtosis of the standardized residual; AIC: Akaike information Criterian value;
SBC: Schwarz Bayesian Information Criterian value; LB-Q(20) / LB-Q^2(20) : Ljung-Box serial correlation test on standardized residual mean and standardized residual mean squared respectively, with 20 lags.

Note: Numbers in brackets are t statistics; Bold numbers are statistically significant.

Table 4.6:Dummy Effects

$$R_t = \alpha + \epsilon_t + return\ spillovers \tag{4.8}$$

where $\epsilon_t \sim N(0, h_t)$, h_t is the conditional variance of the residual.

$$h_t = c_0 + a_1 h_{t-1} + b_1 \epsilon_{t-1}^2 + volatility\ spillovers \tag{4.9}$$

It is demonstrated from Table 4.7 that the above spillover effects in the variance equations of non-overlapping trading sections are all significant. In addition there are mixed results of spillover effects in the mean equations. For the London IPE morning section, there is a significant coefficient of 0.0356 from previous New York market while for NYMEX there is no significant information transmission effect from the IPE morning section. This is a very interesting result. It implies that NYMEX is an efficient market in terms of incorporating London's information. However, this does not seem to be the case for the London market. Previous day's NYMEX trading information has significant effects on IPE open-to-noon section, implying IPE is not so much an efficient market with regard to information incorporation. This result is in line with recent research on stock market behaviour. Eun and Shim (1989) found that "innovations in the US are rapidly transmitted to other markets, whereas no single foreign market can significantly explain the US market movement."

Return transmission effects on the conditional mean and variance of

	IPEOT	IPETC	NYOC	NYOC
Model Specification	GARCH(1,1)	AR|2|-GARCH(1,1)	GARCH(1,1)	GARCH(1,1)
Constant	0.0002 (1.0493)	-0.0005 (-2.8650)	0.0005 (0.9566)	0.0005 (2.9206)
AR(2)		**0.0287** (2.20455)		
Spilllover from NYOC{1}	**0.0356** (2.5985)			
Spilllover from NYOC		**0.8672** (70.47078)		
Spilllover from IPEOT			0.0501 (0.5627)	
Spilllover from IPETC				**1.0073** (77.9025)
GARCH equation				
Constant	**-0.000001** (-3.7482)	-0.000001 (0.7619)	**-0.000004** (-4.9243)	**-0.0000002** (-0.7702)
H(1)	**0.9649** (127.5168)	**0.7243** (18.7520)	**0.9843** (151.7003)	**0.8893** (70.2610)
$E(1)^2$	**0.0141** (2.4868)	**0.1188** (5.3389)	0.0000 (0.0000)	**0.0861** (6.2290)
Spillover	**0.000001** (5.7655)	**0.0157** (4.9610)	**0.000008** (6.6259)	**0.000001** (4.7528)
LL	3181	4084	2380	3245
SK	0.10	0.05	-0.08	-0.01
KU	4.32	1.81	3.85	4.93
LB-Q(20)	23.00	25.83	27.58	27.66
LB-Q^2(20)	31.82	11.50	10.45	14.64

Abbreviations: LL: Log likelihood function value; SK: Skewness of the standardized residual; KU: Kurtosis of the standardized residual; LB-Q(20) / LB-Q^2(20): Ljung-Box serial correlation test on standardized residual mean and standardized residual mean squared respectively, with 20 lags.
Note: Numbers in brackets are t statistics; Bold numbers are statistically significant.

Table 4.7: Spillover Effects

futures returns in contemporaneous trading hours

In addition, information incorporation in overlapping trading hours, ie. the *return information transmission* between IPE afternoon section (IPETC) and NYMEX trading section is also examined. Results of IPETC and NYOC series in Table 4.7 demonstrate that there are substantial return information transmission effects being transmitted between the two markets. In the mean equation the coefficient of information transmission from NYMEX to IPETC is 0.8658 and 1.0073 from IPETC to NYMEX. Information transmission from IPETC to NYMEX is larger than from NYMEX to IPETC. In the variance equation information transmission effects remain significant with similar magnitude to the non-overlapping sections. The results imply that the information transmission effects in over-lapping trading hours are dominant and in both directions. A word of caution, however, is in order when using this result. By including simultaneous trading variables in the system we inevitably introduce bias. Further analysis on the simultaneous trading session with high frequency data is carried out in Chapters 6 and 7.

Joint effects of Monday / Holiday & spillover effects on the conditional mean & variances

Both dummies and volatility spillovers are incorporated in the mean and variance of return series.

$$R_t = \alpha + \epsilon_t + return\ spillovers + dummies \tag{4.10}$$

where $\epsilon_t \sim N(0, h_t)$, h_t is the conditional variance of the residual.

$$h_t = c_0 + a_1 h_{t-1} + b_1 \epsilon_{t-1}^2 + volatility\ spillovers + dummies \qquad (4.11)$$

Spillover or information transmission effects across all series remain robust. Note that the magnitude of the spillover effects in the mean equation is substantially larger than that in the variance equation. Results are displayed in Table 4.8.

Dummy effects also remain consistent with the Monday/Holiday effects discussed previously. Again the magnitude of this contract switching effect is negligible.

4.4.2 Granger causality tests

Chapter 3 introduces the concept of Granger causality. Two variable Granger causality is now further explored using the following test procedure: first find out whether X causes Y to see how much of the current Y can be explained by past values of Y and then decide whether adding lagged values of X can improve the explanation. Y is said to be Granger-caused by X if X helps in the prediction of Y, or equivalently if the coefficients of the lagged Xs are statistically significant. Recall that the statement "X Granger causes Y" does not imply that Y is the effect or the result of X. Granger causality measures predictivity and information content but does not by itself indicate causality in the more common use of the term.

Two pairs of series are tested for Granger causality. Results are shown in Table 4.9. The hypothesis that NYOC does not Granger cause IPEOT is rejected. All other

	IPEOT	IPETC	NYOC	NYOC
Model Specification	GARCH(1,1)	AR|2|-GARCH(1,1)	GARCH(1,1)	GARCH(1,1)
Constant	0.0004 (1.7727)	-0.0004 (-1.983)	0.0002 (0.2728)	0.0004 (2.1516)
AR(2)		**0.0306** (2.3012)		
Spilllover from NYOC{1}	**0.0361** (2.5519)			
Spilllover from NYOC		**0.8663** (69.4602)		
Spilllover from IPEOT			0.0744 (0.8285)	
Spilllover from IPETC				**1.0050** (80.9784)
Mon/Hol Dummy	-0.0006 (-1.2536)	0.0004 (1.0666)	0.0013 (1.1220)	0.0007 (1.8855)
Contract Dummy	-0.0006 (0.5883)	-0.0009 (-1.4960)	0.0015 (0.5819)	0.0002 (0.2543)
GARCH equation				
Constant	-0.000001 (1.0531)	0.000001 (1.1346)	-0.000004 (0.9035)	-0.0000003 (-0.5460)
H(1)	**0.9363** (59.3607)	**0.7129** (16.9756)	**-0.9848** (150.9754)	**0.8822** (63.6749)
$E(1)^2$	**0.0299** (3.2331)	**0.1173** (4.8719)	-0.0000001 (-0.000)	**0.0845** (6.2665)
Spillover	**0.000001** (3.7881)	**0.0164** (4.7868)	**0.000007** (6.2244)	**0.000001** (4.2493)
Mon/Hol Dummy	0.000003 (1.1314)	0.000002 (0.8684)	0.00001 (0.5842)	0.000003 (1.3535)
Contract Dummy	-0.00001 (-1.6316)	-0.00001 (-1.6572)	-0.00004 (1.3840)	**-0.00001** (-2.4009)
LL	3183	4082	2382	3250
SK	0.18	0.05	-0.06	0.00
KU	4.52	1.60	3.92	4.89
LB-Q(20)	20.89	26.23	28.12	29.97
LB-Q^2(20)	34.76	10.59	9.68	14.90

Abbreviations: LL: Log likelihood function value; SK: Skewness of the standardized residual; KU: Kurtosis of the standardized residual;

LB-Q(20) / LB-Q^2(20) : Ljung-Box serial correlation test on standardized residual mean and standardized residual mean squared respectively, with 20 lags.

Note: Bold numbers are statistically significant, Numbers in brackets are *t* statistics.

Table 4.8:Spillover and Dummy Effects

Hypothesis:	F-statistic	Probability
IPEOT does not Granger Cause NYOC	1.19284	0.31243
NYOC does not Granger Cause IPEOT	**6.46509**	4.0E-05
IPETC does not Granger Cause NYOC	0.20728	0.93443
NYOC does not Granger Cause IPETC	0.48344	0.74793

Table 4.9:Pair-wise Granger Causality

sessions accept the null hypothesis of no Granger causality. This result supports our univariate conclusion that there are spillover effects from the previous NYMEX market to the IPE morning session (IPEOT).

Discussion on quality of IPE opening prices and noon prices

The above empirical tests are also carried out using alternatives for IPE opening prices and noon prices. Firstly, average prices of first 5 and 10 minutes opening trades are used as substitue of opening prices. Similar results are found using former prices. However no spillover effects are found from NYMEX previous day using latter prices. This result indicates the up-to-date information is not reflected in IPE opening prices, after 5 minutes' opening. It would take up to 10 minutes for IPE to fully reflect the market information available. Secondly, average prices of last 30 minutes of IPE trades before NYMEX opening is used as an alternative of last 5 minutes trades as IPE noon prices. Same results are obtained, which indicate IPE noon prices reflect current market information efficiently.

As IPE returns for the morning session use both opening prices and noon prices, causion should be exercised when utilise the empirical findings in this chapter due to the possible quaility of IPE opening prices.

4.5 Conclusion

This chapter investigates the simultaneous and non-simultaneous trading sessions of NYMEX and IPE crude oil futures markets within the framework of univariate time series models, using daily data. Evidence of spillovers in mean returns is found in the IPE morning session, where up to two previous days' NYMEX information has significant effects. This finding should be treated with caution and will be further investigated using a different time series (multivariate) framework in the next chapter. In the analysis of information transmission from IPE morning to NYMEX, NYMEX is found to be efficient in incorporating past information.

When both markets are open, i.e. the IPE afternoon trading session and NYMEX day trading session, substantial information transmission effects in the mean take place in both directions. This may imply the existence of a common trading market place. In addition, there is no evidence of Monday / Holiday effects in all trading sessions, but marginally significant negative contract-switching effects in the variance equations NYMEX trading session.

Evidence of volatility transmission in the variance equation of the return series is found in all trading session. However the magnitudes of these effects are negligible, therefore, not further investigated in this thesis.

Evidence provided by the data available so far in this chapter seems to indicate that daily information transmission from NYMEX has an edge over IPE, at least so far as the IPE morning section is concerned. To further investigate the observed results, two research directions are identified as follows: (1) analysis on information transmission effects between IPE morning trading session and NYMEX open-close trading session, which will be carried out in Chapter 5; (2) research on simultaneous trading hours with high frequency data (eg. every 5 minutes) in order to establish the true market leader, which will be carried out in detail in Chapters 6 and 7.

Chapter 5
Vector Autoregressive Analysis

5.1 Introduction

This chapter utilizes a multivariate framework to further investigate the spillover effects between IPE and NYMEX that have been detected in Chapter 4. In particular Vector Autoregressive (VAR) modelling is applied to achieve the objective.

VAR paints a general picture on a system of variables that interact with each other. It takes into account the dynamic relationship among variables in the system. It is effectively a reduced-form time series formulation of a linear structural model of the variables in question that can be estimated by ordinary least squares. In this chapter, a two-variable VAR is analyzed to uncover the dynamic interaction and possible lead-lag relationship between IPE morning session and NYMEX trading session.

This chapter is organized as follows: Section 5.2 discusses briefly the literature that has applied VAR methodology, its advantages and disavantages; Section 5.3 presents data used in this chapter; Section 5.4 conducts empirical analysis and market behaviour over time; and Section 5.5 draws the conclusions.

5.2 Literature review and methodology

Vector autoregressive (VAR) is a powerful time series analysis tool since Sims' (1980) influential work. It is an alternative to the traditional simultaneous equation structural system. Sims' main criticism on the latter type of analysis is that macroeconometric models are often not based on sound economic theories or the available theories are not capable of providing a completely specified model.

In situations where an economic theory is not available to specify the model, statistical tools must be applied instead. This approach sets up a fairly loose model which does not impose rigid a *priori* restrictions on the data generation process, then use the statistical tools to determine possible constraints. VAR represents a class of loose models that may be used in such an approach.

5.2.1 Introducing VAR

Vector Autoregressive representation (VAR) is analogous to autoregressive analysis of univariate time series. It has the following representation:

$$Y_t = C + A_1 Y_{t-1} + A_2 Y_{t-2} + \ldots + A_k Y_{t-k} + \varepsilon_t \tag{5.12}$$

where $Y_t = \begin{bmatrix} y_{1t} \\ \cdots \\ y_{nt} \end{bmatrix}, \quad \varepsilon_t = \begin{bmatrix} \varepsilon_{1t} \\ \cdots \\ \varepsilon_{nt} \end{bmatrix}$

As in univariate analysis, the vector autoregressive system can be written in Vector Moving Average - VMA(∞) form as follows (See Hamilton 1994):

$$Y_t = \mu + \varepsilon_t + \Psi_1 \varepsilon_{t-1} + \Psi_2 \varepsilon_{t-2} + ... + \Psi_k \varepsilon_{t-k} \tag{5.13}$$

Therefore, the matrix Ψ_k has the following derivation

$$\frac{\partial Y_{t+k}}{\partial \varepsilon_t} = \Psi_k \tag{5.14}$$

This formula can be interpreted as: the element (i, j) of matrix Ψ_k identifies the effects of a one unit increase in the jth variable's innovation at date $t(\varepsilon_{jt})$ on the value of the variable i, k periods later (Y_{i+k}).

A collection of the parameters (i, j) of Ψ_k make up the impulse response function which is defined below.

The **impulse response function** is a plot of the element (i, j) of matrix Ψ_k as a function of k. It describes the response of $y_{i,t+k}$ to a one-time impulse in y_{jt} with all other variables dated t or earlier held constant. It is a useful means to isolate, measure and compare the effects of the variables in the system to innovations or shocks to the residuals.

A common practice when using impulse response functions is the orthogonalization on the residuals across the equations in the system to get around the often correlated residuals across equations. By orthogonalization we obtain the orthogonalized impulse response function. This function is based on the decomposition of the original VAR innovations $(\varepsilon_{1t}, \varepsilon_{2t}, ...\varepsilon_{nt})$ into a set of uncorrelated components $(u_{1t}, u_{2t}..., u_{nt})$

and then calculate the responses of Y_{t+k} to unit impulse in u_{jt}. Popular orthogonalization processes are the Choleski lower diagonal decomposition; the Bernanke (1986) and the Blanchard & Quah (1989) decompositions.

The impulse response analysis is one of the two pillars in VAR analysis. The second one is the variance decomposition analysis.

Variance decomposition tells us the proportion of the movements in a sequence due to its "own" shocks versus shocks to the other variables. More specifically, it calculates the contribution of the jth orthogonalized innovation to the mean-squared-error (MSE) of the s-period-ahead forecast:

The s period forecast error in a VAR system is

$$Y_{t+s} - \hat{Y}_{t+s|t} = \varepsilon_{t+s} + \Psi_1 \varepsilon_{t+s-1} + \Psi_2 \varepsilon_{t-2} + ... + \Psi_{s-1} \varepsilon_{t+1} \tag{5.15}$$

and the mean squared error of the s period forecast is thus

$$MSE(\hat{Y}_{t+s|t}) = E[(Y_{t+s} - \hat{Y}_{t+s|t})(Y_{t+s} - \hat{Y}_{t+s|t})'] = \Omega + \Psi_1 \Omega \Psi_1' + \Psi_2 \Omega \Psi_2' + ... + \Psi_{s-1} \Omega \Psi_{s-1}'$$

where

$$\Omega = E(\varepsilon_t \varepsilon_t') \tag{5.16}$$

Suppose ε_t is $n \times 1$ orthogonalized residual, then the contribution of jth order of innovation to the mean-squared-error (MSE) of the s-period-ahead forecast would be

$$var(\varepsilon_{jt}) * (\Psi_1\Psi_1' + \Psi_2\Psi_2' + ... + \Psi_{s-1}\Psi_{s-1}') \tag{5.17}$$

Effectively, the variance decomposition is another innovation accounting in the VAR system, equivalent to Impulse Response Function presented in Equation 5.14.

By analyzing the impulse response function and variance decomposition, researchers can trace out the effects of shocks to individual variables in the system over time. They are particularly useful in macroeconomic policy analysis. In this chapter impulse response analysis and variance decomposition are conducted to trace the effects of innovations of one market to the other over time, how long it takes for one unit measure of innovation to die down. The results can be considered as an indication of lead-lag relationship between IPE morning session and NYMEX from another view point.

5.2.2 Criticism of VAR methodology

One criticism of orthogonalization is that there are potentially many different ways to achieve the zero covariance across the residuals and the resulting impulse response functions can be different from each other. These orthogonalization assumptions are considered to have no economic rationale - they are *atheoretical*, using the term of Cooley and LeRoy(1985). This shortcoming is directly linked to the setup of the VAR - it is a statistical model. Various authors have developed structural VAR which combine economic considerations with VAR by allowing contemporaneous relationships in the system. The key in this kind of system is to identify the contemporaneous relationships from the reduced form by imposing various restrictions according to underlying economic theories. For example, Bernanke (1986) and Blanchard (1989) impose restrictions on short run impact of shocks to variables under consideration, Blanchard and Quah (1989) designed restrictions that allow for long run effects in the system. Swanson and Granger (1997) construct a method that combines both prior economic knowledge and statistical analysis of the VAR residuals.

Another criticism of VAR is that the impulse response function varies with different ordering of residual variables. It may cause difficulties when interpreting the results. An alternative method is proposed by Pesaran and Shin (1996), and Koop, Pesaran and Potter (1996) to use the generalized impulse response which is invariant to the ordering of the variables. These above-mentioned new methodologies are not discussed further in this chapter as the criticisms to VAR do not apply in relation to our investigation in the interaction between IPE morning and NYMEX, and they are thus omitted.

Choleski decomposition is chosen as the orthogonalization for the residuals of the two return variables in this chapter: IPE morning returns and NYMEX daily returns. There two variables have the natural time gap in opening hours, which provides us with the natural ordering of the variables: first variable is the IPE morning return series; the second variable is the NYMEX open-close return series. This lower diagonal decomposition implies the innovations of IPE morning return may have temporal influence on the innovations of NYMEX variable while there is no same day feedback from NYMEX innovations to IPE morning innovations.

5.3 Data

Two return data series are used in this empirical work. They are the IPE morning log return series and NYMEX open-close log return series. As specified in the previous chapter IPE morning return series are calculated as the log return of IPE opening prices to IPE morning closing prices. The IPE morning closing prices are constructed as the average of the last half - hour [3] IPE trading prices before 14:45 London time, when NYMEX opens. Estimation period is from 4th January 1994 to 29th December 2000. Descriptive data statistics of the two series are listed in Table 5.10. As indicated in the table both series have fat tails with Kurtosis values greater than 3. Both have serial correlation with significant Lung-Box Q tests on 5 lag residuals. NYMEX return demonstrates negative skewness while IPE morning return has positive skewness. Note that the return series used in this chapter is an extension to those that are analyzed in Chapter 4[4].

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[3] In the previous chapter, 5-minute averages are used as the closing price for IPE morning session. It was suggested that 30-minute average is a better approximation to the IPE closing price for the morning as the former is too close to the NYMEX opening time not to be influenced by NYMEX activities. Similar results are obtained with there two versions of data. See discussion on quality of data of IPE in Section 4.4.

[4] Analysis in Chapter 4 has been published (See Lin and Tamvakis, 2001) using the most up-to-date data at the time. Further research on extended data is not necessary as the results are carefully incorporated in this chapter.

	IPEOT	**NYOC**
Mean	0.0005235	0.0002134
Variance	0.0000599	0.000305
Skewness	**0.2411** (Sk=0) (ρ =0.0000)	**-0.11829** (Sk=0) (ρ =0.0464)
Kurtosis	**3.9185** (Ku=0) (ρ =0.0000)	**1.48089** (Ku=0) (ρ =0.0000)
LB-Q(5)	**11.1556** (ρ = 0.04838)	**14.1335** (ρ =0.01478)
LB-Q(10)	18.0476 (ρ = 0.05416)	14.6387 (ρ =0.14580)
LB-Q(5)/LB-Q(10): Ljung-Box serial correlation test, with 5/10 lags. Note: the numbers in bold are statistically significant.		

Table 5.10:Descriptive Data Analysis

Head	**LR test**	**AIC**	**SBC**
6 lags	6 v 5, 2.925 (ρ =0.5704)	-12.14556	-12.06250
5 lags	5 v 4, 3.147 (ρ =0.5334)	-12.14619	-12.07595
4 lags*	**4 v 3, 13.195 (ρ =0.0103)**	**-12.14903**	-12.09156
3 lags	3 v 2, 12.725 (ρ =0.0126)	-12.14594	-12.10124
2 lags	2 v 1, 7.789 (ρ =0.0996)	-12.14314	**-12.11121**

Table 5.11:Lag Length Tests

5.3.1 Lag Length

For the purpose of the VAR analysis in this chapter, 4 lags are used. It is derived from the likelihood ratio test, Akaike Information Criterion (AIC), and the Schwartz Bayesian Criterion (SBC). Test results are shown in Table 5.11. LR and AIC tests indicate 4 lags as the appropriate lag length while SBC test indicates 2 lags as the appropriate length. Residual analysis indicates there is some serial correlation in the 2 lag specification while the 4 lag specification is clear of serial correlation problems. Therefore 4 lags are used in the VAR modeling throughout this chapter.

5.4 Empirical findings

5.4.1 Estimation and Granger Causality

A two-variable, four-lag VAR system is set up as follows:

$$ipeot_t = a_0+a_1ipeot_{t-1}+a_2ipeot_{t-2}+a_3ipeot_{t-3}+a_4ipeot_{t-4}+c_1nyoc_{t-1}+ \quad (5.18)$$

$$c_2nyoc + c_3nyoc_{t-3} + c_4nyoc_{t-4}$$

$$nyoc_t = c_0 + a_1 ipeot_{t-1} + a_2 ipeot_{t-2} + a_3 ipeot_{t-3} + a_4 ipeot_{t-4} + c_1 nyoc_{t-1} + \quad (5.19)$$

$$c_2 nyoc + c_3 nyoc_{t-3} + c_4 nyoc_{t-4}$$

Generalized Method of Moments (GMM) is used to correct any possible distortions in the standard error, caused by heteroskedasticity in the residuals of the VAR system. The VAR results are shown in Table 5.12. In the IPE morning return equation, there are three significant lags, one from its own and two from NYMEX returns. Granger causality test, in this framework, is a joint hypothesis that each of all lags of NYMEX are jointly equal to zero, ie. $c_1 = c_2 = c_3 = c_4$. It is not rejected in the IPE morning return equation. In the NYMEX return equation, there are two significant lags, one from its own and one from the IPE morning returns. Again Granger causality test, which is a joint test of $a_1 = a_2 = a_3 = a_4$, is rejected marginally. These Granger causality results are opposite from what we observe in Chapter 4. Recall from Chapter 4 that there are significant spillover effects from NYMEX return of previous day to IPE morning return but not the other way around.

Looking carefully at the results we can observe that the rejection of the no Granger causality hypothesis from IPEOT to NYMEX is of marginal significance $\rho = 0.048$ and the acceptance of no Granger causality hypothesis from NYMEX to IPEOT is not very strong with $\rho = 0.1024$. Given that the estimation period in this chapter is almost twice as long as in the univariate analysis of Chapter 4, further analysis is to be carried out in section 5.4.3 on two separate time periods to uncover whether the observed different results are due to different estimation methods or due to different estimation periods.

5.4.2 Impulse Response Functions and Variance Decomposition

After identifying the causal relationship between the variables in the above session, we analyze how innovations of one market are transmitted to the other market by the impulse response function and variance decomposition analyses.

Graph 5.3 displays effects of one standard deviation shocks of NYMEX to IPE morning and vice versa. Table 5.13 displays the variance decomposition results. Features that emerge from the graph and the table are that: (1) all responses are small in magnitude and die out after 6 lags of initial shocks, indicating both markets are efficient in information incorporation on a daily basis; (2) the magnitude of responses of IPEOT to NYMEX innovations is larger than the magnitude of responses of NYMEX to IPEOT innovations which is consistent with our one way Granger causality test result in Section 5.4.1.

5.4.3 Market behaviour over time

To check whether the observed market behaviour observed above changes over time, the estimation period is divided into 2 and each sub-period is re-estimated using the above methodology. First sub-period is from 12/01/1994 to 30/06/1997 and the second

Coefficients	**IPE morning return**	**NYMEX return**
a_1	0.02728	-0.02499
	(0.78832)	(-0.37583)
a_2	0.01187	-0.09467
	(0.29315)	(-1.54035)
a_3	**-0.06123**	-0.04961
	(-2.09353)	(-0.85659)
a_4	0.01963	**-0.13374**
	(0.70801)	(-2.37533)
c_1	0.01271	0.04769
	(0.93785)	(1.92008)
c_2	-0.01357	0.01676
	(-1.03901)	(0.59810)
c_3	**-0.02439**	0.00703
	(-2.23263)	(0.27466)
c_4	-0.00141	**0.05696**
	(-0.12628)	(2.29610)
a_0/c_0	**0.00051**	0.00041
	(2.80836)	(0.97843)
Granger causality test (LM test)	IPEOT does not Granger cause NYMEX	$\chi^2(4)$=**9.56381** (**ρ=0.0484**)
Granger causality test	NYMEX does not Granger cause IPEOT	$\chi^2(4)$=7.71926 (ρ=0.1024)
Note: equation is specified as: IPEOT/NYMEX$_t = a_0/c_0$ $+a_1\text{IPEOT}_{t-1} + a_2\text{IPEOT}_{t-2} + a_3\text{IPEOT}_{t-3} + a_4\text{IPEOT}_{t-4}$ $+c_1\text{NYOC}_{t-1} + c_2\text{NYOC}_{t-2} + c_3\text{NYOC}_{t-3} + c_4\text{NYOC}_{t-4}$		
Observation from 12/01/94 to 29/12/2000; Numbers in bold indicate significant parameters.		

Table 5.12: VAR Estimation Results and Granger Causality Tests (all observations)

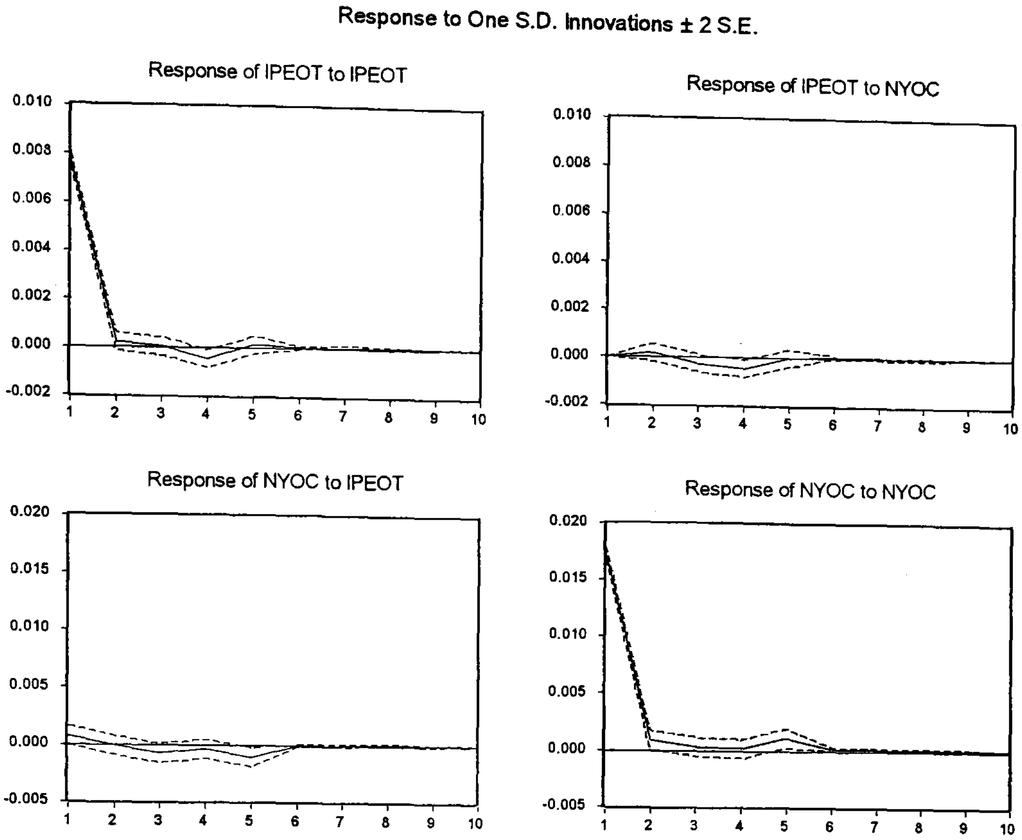

Figure 5.3: Impulse Response Functions (all observations)

Variance decomposition of IPEOT			Variance decomposition of NYOC	
Period	**IPEOT**	**NYOC**	**IPEOT**	**NYOC**
1	100.0000	0.000000	0.188568	99.81143
2	99.94357	0.056430	0.190636	99.80936
3	99.80536	0.194640	0.401178	99.59882
4	99.44710	0.552905	0.448851	99.55115
5	99.44585	0.554152	0.832219	99.16778
6	99.44518	0.554822	0.833128	99.16687
7	99.44520	0.554801	0.834485	99.16551
8	99.44311	0.556891	0.834668	99.16533
9	99.44305	0.556950	0.837267	99.16273
10	99.44303	0.556968	0.837337	99.16266

Table 5.13:Variance Decomposition (all observations)

sub-period is from 1/07/1997 to 29/12/2000. The results for the first and second sub-periods[5] are shown in Table 5.14 and Table 5.15 respectively.

Results of first sub-period estimation from Table 5.14 imply the following: (1) in the case of IPE morning return, there are no significant own lag coefficients, however there are a number of NYMEX return lag coefficients which are significant to the IPE morning returns, indicating NYMEX is the leader market. Granger causality in the two-variable VAR system confirms the above results: LM test on the hypothesis of NYMEX does not Granger cause IPEOT is strongly rejected with χ^2 value of 22.42; (2) in the case of NYMEX return series, again there are no significant own lag coefficients and the effects of IPE morning trading session are not significant to NYMEX trading either with one marginal exception. This result is also reflected in the Granger causality test from IPE morning returns to NYMEX trading returns. The hypothesis of Granger causality from IPE morning to NYMEX trading is not rejected. The one way Granger causality from NYMEX to IPE morning session is consistent with our univariate analysis in Chapter 4 that there are spillovers from NYMEX previous day to IPE morning, but no information of IPE morning return series is transmitted to NYMEX return series. Further analysis on the period from 30th Jun 97 to 29th December 2000 is conducted. Results are shown in Table 5.15.

The 2nd sub-period estimation results indicate: (1) in the case of IPE morning returns, there are no significant coefficients either for its own lags or for NYMEX

[5] To facilitate the comparison between univariate and multivariate analyses in Chapter 4 the two sub-periods are almost half and half incidentally.

	IPE morning return	**NYMEX daily return**
$IPEOT_{t-1}$	0.06712 (1.59994)	-0.06148 (-0.51536)
$IPEOT_{t-2}$	-0.00788 (-0.26121)	-0.03935 (-0.38240)
$IPEOT_{t-3}$	**-0.07548** (-2.30260)	**-0.19228** (-2.08725)
$IPEOT_{t-4}$	0.00001 (0.00037)	0.04368 (0.44724)
$NYOC_{t-1}$	**0.03292** (2.57159)	0.04252 (1.21263)
$NYOC_{t-2}$	**-0.04515** (-3.23898)	0.06375 (1.61909)
$NYOC_{t-3}$	**-0.03012** (-2.58812)	-0.03845 (-1.01178)
$NYOC_{t-4}$	-0.00105 (-0.08689)	0.03151 (0.90172)
Constant	0.00026 (1.29032)	0.00066 (1.23339)
Granger causality test (LM test)	IPEOT does not Granger cause NYMEX	$\chi^2(4)$=4.843448 (ρ =0.30374117)
Granger causality test	NYMEX does not Granger cause IPEOT	$\chi^2(4)$=**22.424782** (ρ =0.00016494)
Note: equation is specified as: $IPEOT/NYMEX_t = a_0 + a_1 IPEOT_{t-1} + a_2 IPEOT_{t-2} + a_3 IPEOT_{t-3} + a_4 IPEOT_{t-4} + c_0 + c_1 NYOC_{t-1} + c_2 NYOC_{t-2} + c_3 NYOC_{t-3} + c_4 NYOC_{t-4}$		
Observations from 12/01/1994 to 30/06/1997, Numbers in bold are statistically significant.		

Table 5.14:VAR Estimation (1st sub-period)

cross lags; (2) in the case of NYMEX returns, there are two significant coefficients, one for the 4th own lag, and the other for the 4th lag of IPE return series. In this time period, the hypothesis of no Granger causality from NYMEX to IPEOT is not rejected with significance level $\rho = 0.7950$ while the hypothesis of no Granger causality from IPEOT to NYMEX is rejected with significance level $\rho = 0.01481$. Note that these results of Granger causality are directly opposite to those in the 1st sub-period.

The opposite direction of Granger causality between IPE and NYMEX in the two sub-periods are strongly established. It indicates very different information transmission behaviour in these two sub-periods. Recall the marginal significance of the Granger Causality results from section 5.4.1 which use all observations available which can be interpreted as the average of the different market behaviour of the two sub-periods.

5.4.4 Impulse response and variance decomposition over time

Impulse response for the two sub-periods are shown in Figure 5.4 and 5.5 and variance decomposition for the two sub-periods are listed in Table 5.16. Comparing the figures from the two sub-periods two distinctive features emerge: (1) effects from NYMEX to IPE morning session are larger in the first sub-period than in the second sub-period, both initially and consistently in longer lags. (2) effects from IPE morning session to NYMEX are smaller in the first sub-period than in the second sub-period, both initially and consistently in longer lags. The observed features further confirm the estimation results in the previous section. It should be noted that the magnitudes in percentage

	IPE morning return	NYMEX return
IPEOT_{t-1}	0.01956 (0.44780)	-0.02108 (-0.26335)
IPEOT_{t-2}	0.01163 (0.21734)	-0.10803 (-1.47483)
IPEOT_{t-3}	-0.05648 (-1.49356)	0.00865 (0.12095)
IPEOT_{t-4}	0.02655 (0.74744)	**-0.21271** (-3.14918)
NYOC_{t-1}	0.00065 (0.03131)	0.05900 (1.72994)
NYOC_{t-2}	0.00691 (0.35891)	-0.01799 (-0.47775)
NYOC_{t-3}	-0.02028 (-1.26377)	0.03430 (0.99739)
NYOC_{t-4}	0.00241 (0.14192)	**0.07606** (2.21703)
Constant	**0.00075** (2.45197)	0.00022 (0.34275)
Granger causality test (LM test)	IPEOT does not Granger cause NYMEX	$\chi^2(4)$=**12.3688** (ρ= 0.0148)
Granger causality test	NYMEX does not Granger cause IPEOT	$\chi^2(4)$=1.6762 (ρ=0.7950)
Note: equation is specified as: $\text{IPEOT/NYMEX}_t = a_0 + a_1\text{IPEOT}_{t-1} + a_2\text{IPEOT}_{t-2} + a_3\text{IPEOT}_{t-3} + a_4\text{IPEOT}_{t-4} + c_1\text{NYOC}_{t-1} + c_2\text{NYOC}_{t-2} + c_3\text{NYOC}_{t-3} + c_4\text{NYOC}_{t-4}$		
Observations from 01/07/1997 to 29/12/2000; Numbers in bold are statistically significant.		

Table 5.15:VAR Estimation (2nd sub-period)

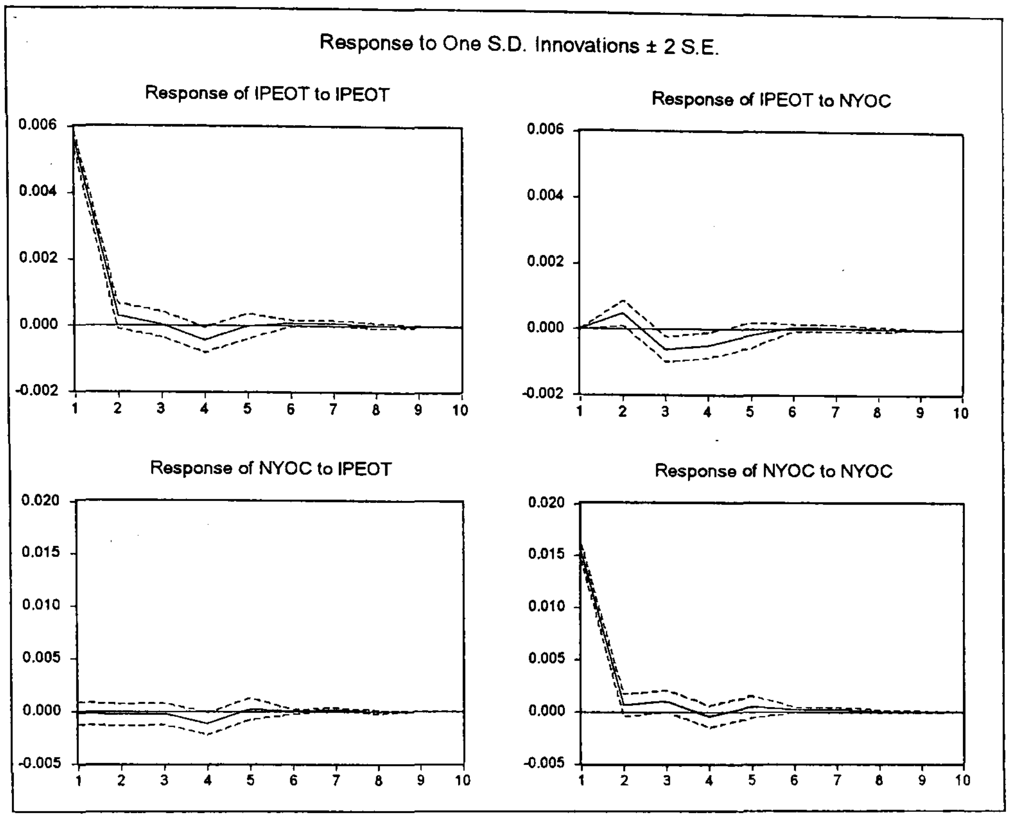

Figure 5.4: Impulse Response Function (1st sub-period)

terms are quite small, in the range of 0.55% - 2.59%. Caution should be exercised when applying the results.

5.5 Conclusion

This chapter applies VAR analysis to IPE morning return series and NYMEX open-close return series. Estimation using all data available suggests different results from Chapter 4. Subsequent sub-period estimation results depict different information trasmission behaviour. The first sub-period mirrors the results from Chapter 4. It thus can be implied that the estimated results using all available information are averages of the behavour of the two sub-periods. This changing behaviour from one sub-period to the

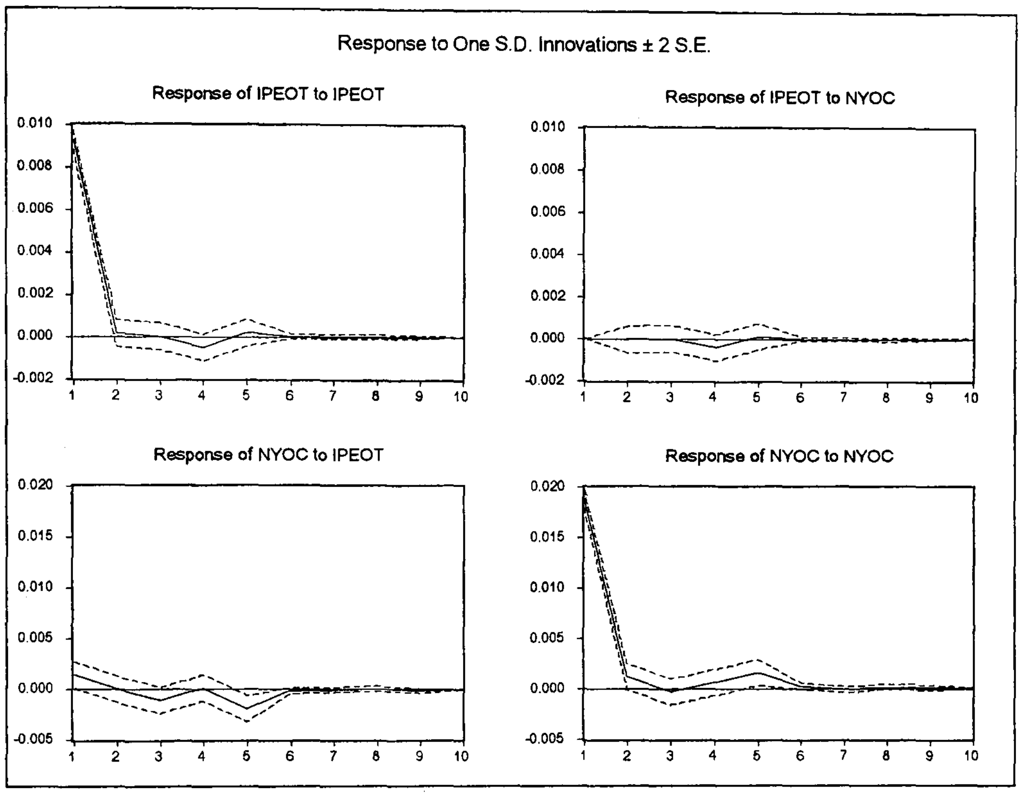

Figure 5.5: Impulse Response Function (2nd sub-period)

	First sub_estimation period				Second sub_estimation period			
	Variance decomposition of IPEOT		Variance decomposition of NYOC		Variance decomposition of IPEOT		Variance decomposition of NYOC	
Per	**IPEOT**	**NYOC**	**IPEOT**	**NYOC**	**IPEOT**	**NYOC**	**IPEOT**	**NYOC**
1	100.0000	0.000000	0.015634	99.98437	100.0000	0.000000	0.560831	99.43917
2	99.27815	0.721853	0.066058	99.93394	99.99713	0.002868	0.558512	99.44149
3	98.06921	1.930788	0.093078	99.90692	99.99705	0.002951	0.918589	99.08141
4	97.29199	2.708008	0.695629	99.30437	99.78371	0.216287	0.921749	99.07825
5	97.18898	2.811020	0.716145	99.28385	99.77224	0.227761	1.919709	98.08029
6	97.18338	2.816623	0.716869	99.28313	99.77207	0.227931	1.924642	98.07536
7	97.18012	2.819884	0.724753	99.27525	99.77199	0.228006	1.926928	98.07307
8	97.18010	2.819898	0.726882	99.27312	99.76938	0.230623	1.927674	98.07233
9	97.17908	2.820921	0.726884	99.27312	99.76933	0.230667	1.938586	98.06141
10	97.17886	2.821140	0.727064	99.27294	99.76933	0.230675	1.939013	98.06099

Table 5.16:Variance Decomposition for Two Sub-period Estimation

next points to a possible structural break between the two sub-periods. Given that there are no significant political forces such as "oil shocks" taking place during the period under investigation, the changing forces must be coming from the markets themselves. It is an interesting topic but beyond the scope of this thesis.

Chapter 6
High Frequency Lead-Lag Analysis

6.1 Introduction

Previous chapters have investigated the relationship between IPE and NYMEX on the basis of daily open-close return series and spillover effects are found in the analysis carried out in Chapters 4 and 5. In this chapter, emphasis is put on the simultaneous trading sessions of IPE and NYMEX, i.e. IPE afternoon return series and NYMEX return series, in particular, intra-day high frequency lead-lag analysis is conducted. The reason for applying this methodology is two-fold: (1) as explained earlier, because news arrives in the market place in a matter of seconds, information incorporation is expected to take place in a very short period of time. Thus the need for intra-day high frequency analysis to detect the lead-lag relationship is desirable; (2) from the point of view of methodology adoption, conventional methodology with daily frequency data is not suitable to uncover dynamic interactions between NYMEX futures and IPE futures when both markets are trading simultaneously due to the fact that the return series of the two markets are endogenous variables and should be determined jointly, and there is a lack of quality exogenous variables that can be used to identify the temporal relationship between the two return series.

Section 6.2 conducts a brief literature review; Section 6.3 introduces the high frequency data applied in this investigation; Section 6.4 briefly reviews the methodology applied in this chapter and empirical findings both in general and in special "event days"; and Section 6.5 concludes.

6.2 Literature review

Recall from the review on the methodology of the lead-lag relationship conducted in Chapter 3, one of the methodologies discussed is the high frequency lead-lag analysis, which is expressed using the following formula:

$$R_{A,t} = \alpha + \sum_{k=-n}^{n} \beta_k R_{B,t+k} + \epsilon_t \tag{6.20}$$

where $R_{A,t}$ is the return of asset A at time t, $R_{B,t}$ is the return of asset B at time t; k is the number of time periods that are used to test the length of leads and lags. There are n leads and n lags being tested in this equation. The coefficients with positive subscripts $\beta_1, ...\beta_n$ are lead coefficients and those with negative subscripts $\beta_{-1}, ...\beta_{-n}$ are lag coefficients. If lead coefficients are significant then A leads B, meaning A has predictive power over B. If lag coefficients are significant then A lags behind B, meaning that B has predictive power over A.

This method is proposed by Stoll and Whaley(1990) and Chan(1992) and is simple to apply to the detection of lead-lag relationship between IPE and NYMEX. The speed and magnitude of information transmission is estimated and results are analyzed in the following section.

Prior research on the lead-lag relationship has also investigated the news effects on the relationship. For example, Chan (1992) investigates the lead-lag relationship between stocks and stock index futures around macroeconomic information releases and finds that the stock index futures market leads the underlying stock index due to the leverage and low transaction cost advantages of the futures market. Grünbichler et al (1994) examine the same relationship in the case of firm-specific information. Their results indicate the lead-lag relationship is influenced by different news effects.

In this chapter the lead-lag relationship is examined both with and without the arrival of demand and supply news, in order to detect any changes of behaviour of the underlying information transmission mechanism.

6.3 Data

6.3.1 Data source

High frequency data for IPE afternoon are extracted from the tick by tick CD rom produced by IPE. This data set consists of bid-offer price ranges and transaction price, and are time stamped to the second. NYMEX data are obtained from Tickdata.com., a US vendor. This data set includes trade data only, which are time stamped to the nearest minute. Only nearby contracts from both markets are selected. To match the trading time of two futures contracts, holidays are discarded from data sets and early closing days are adjusted to keep the common trading hours. The data range for the study is from 4th January 2000 to 29th December 2000, reflecting the most up-to-date data available. A total of 244 common trading days are included in the data sets.

6.3.2 Return series

5-minute return series are constructed and then analyzed. The 5-minute interval is chosen due to (1) it is small enough to catch temporal relationship between two contracts; (2) it is large enough to mitigate the possible errors-in-the-variables problem caused by non-synchronous trading of the two futures contracts as well as the bid-offer bounce problem. Bid-offer bounce occurs in tick by tick data where one buy order is often followed by one sell order, and as a result, a false return pattern can be generated.

Each NYMEX and IPE simultaneous trading day is partitioned into 5-minute intervals. The first 10 minutes' and last 20 minutes' worth of trading prices are skipped to avoid the open and close effects. The reason is that at both opening and closing there exist information discovery processes, which may distort the information transmission mechanism between the two markets. At the NYMEX opening there exists the need to incorporate information accumulated overnight. Although NYMEX ACCESS makes trading available overnight the provision is not continuous, the volume of trading is limited and thus price discovery process is restricted. At the market closing there is the need to unwind the daily position, balance the books etc to satisfy trading requirements that are set up by individual companies. Furthermore, the last 20 minutes' worth of trading prices on NYMEX are not complete due to problems with data reporting. For these reasons the opening and closing data are not analyzed and we are testing the lead-lag relationship for the middle trading session of the two markets, ie. from 15:00 to 19:50 GMT.

In each of the 5-minute intervals the last trade price is recorded. If there are no trades taking place in an interval, the last interval price is used as the current interval price. Due to the lack of bid-ask prices for NYMEX contracts, only trades data are analyzed in this study.

The extracted trade prices are then used to generate the time series of log returns for both IPE and NYMEX. The log return is the logarithmic ratio of the last trade price of the current 5-minute interval and the last trade price of the previous 5-minute interval. If there are no trades in an interval, zero returns are recorded. If there are substantial zero returns due to null trades, a false return bias toward zero could be generated. However, the selection of 5 minutes as the interval mitigates this problem. As can be seen from the descriptive analysis in Table 6.17, null trade intervals account for only 3.5% and 0.3% of observations for IPE and NYMEX respectively, which should not cause any bias concerns for the analysis of lead-lag relationship.

Although of no concern for the analysis of lead-lag relationship, the percentage of null trades does reflect the trading frequency of the markets. With the lack of accurate data on intra-day transaction volume for both contracts, this percentage information and the average number of trades within each 5 minute interval are used as

Sample autocorrelation of 5 minute returns of NYMEX and IPE afternoon		
	IPE afternoon	NYMEX
Mean	-0.000002	0.0000076
Variance	0.0000046	0.0000064
Skewness	-0.36477	-0.30987
Kurtosis	7.41422	6.03270
Average trades in a 5min interval	7.16	20.64
% of no trades in 5min intervals	3.5%	0.3%
(for details see Section 6.3.2)		

Table 6.17:Descriptive Data Analysis of 5-minute Returns of NYMEX and IPE Afternoon Session

measures of trading activities. As displayed in Table 6.17 IPE afternoon has an average of 7 trades per 5 minute interval, almost one third of NYMEX's trading intensity of 21 trades per 5 minute interval. These two trading intensity measures indicate that IPE afternoon trading volume is less than that of NYMEX. So is its liquidity and market depth.

Descriptive analysis of both return series are displayed in Table 6.17. As expected basic statistics for the two contracts are similar. Significant negative skewness and positive kurtosis are demonstrated, suggesting the existence of fat tails and asymmetry in both series.

Next, autocorrelation is calculated for 1 to 12 lags. In the case of NYMEX return series, to avoid the contamination of the overnight trading gap and to keep the consistency of return comparability, early returns data of each trading day are skipped according to the order of autocorrelation. First return data are skipped when estimating first autocorrelation. A further 244 returns are dropped each time with the increase of one lag length at a time. A total of 13551 observations are used for serial correlation

Lag	Number of observations	IPE afternoon return	NYMEX return
1	13551	-0.0101432	**-0.0712830***
2	13307	-0.0398004*	**-0.0163232***
3	13063	-0.0012367	0.0065024
4	12819	-0.0122893	-0.0117234
5	12575	-0.0052916	-0.0127537
6	12331	-0.0028834	0.0008400
7	12087	0.0020914	-0.0006816
8	11843	0.0016441	-0.0005766
9	11599	-0.0238500	-0.0076684
10	11355	-0.0080944	-0.0054612
11	11111	0.0196534	0.0142029
12	10867	-0.0030245	-0.0119406
Asymptotic standard errors for the correlation coefficients can be approximated by the square root of the reciprocal of the number of observations, in this case, 10867 observations.			
The significance of t distribution of the serial correlation at 0.001 level is 3.09 and is indicated by "*". The reason for using 0.1% level of significane is from Lindley (1957) who points out, for large samples lower significance may be required.			

Table 6.18:Autocorrelation of 5minute Returns of NYMEX and IPE Afternoon Session

of 1 lag and a total of 10864 observations are used for serial correlation estimation for 12 lags. Same considerations are given when calculating the autocorrelation of IPE afternoon return series. Results are displayed in Table 6.18. Significant negative serial correlation is detected in lag 2 of the return series of IPE contracts as well as lags 1 and 2 of the NYMEX return series. It may be caused by the bid-offer bounce problem which is documented in Stoll & Whaley (1990) and Chan(1992). Without bid - ask quotations for NYMEX contracts it is difficult to estimate or correct this problem. Caution should be exercised when interpreting these results.

$\rho(r\_ipe_t, r\_nymex_{t+k})$, Number of observations =10867			
Lag k	ρ	**Lag k**	ρ
-12	-0.0047974	0	0.6461377 *
-11	0.0163493	1	0.1602770 *
-10	-0.0186745	2	-0.0009434
-9	-0.0243995	3	-0.0150262
-8	0.0016001	4	-0.0147552
-7	0.0051930	5	-0.0088828
-6	-0.0142872	6	-0.0112132
-5	-0.0170264	7	-0.0108172
-4	-0.0162990	8	0.0071801
-3	0.0030275	9	-0.0133717
-2	-0.0059128	10	-0.0105897
-1	0.0153041	11	0.0015882
		12	0.0041056

ρ is the cross correlation between IPE afternoon 5 minutes returns and NYMEX 5 minutes returns.
ρ_{t+k} is correlation between current IPE afternoon return and past (future) NYMEX returns when k is negative (positive).
Asymptotic standard errors for the cross-correlation coefficients can be approximated by the square root of the reciprocal of the number of observations, in this case, 10867 observations.
The significant ρ is indicated by "*" at 0.001.

Table 6.19:Serial Correlation between the 5-minute Returns of NYMEX and IPE Afternoon

6.3.3 Cross correlation

Cross correlation up to 12 lags between IPE return series and NYMEX return series are calculated and displayed in Table 6.19. It provides a preliminary outline of the lead-lag relation between the two markets and suggests the order of lead-lag relation in later regression. Contemporaneous cross correlations between IPE and NYMEX is high with significant value of 0.646. The other significant cross correlation is of order 1, indicating there will be at least one lag being included in the regression.

6.4 Methodology and empirical findings

6.4.1 High frequency lead-lag analysis

High frequency lead-lag analysis proposed by Stoll and Whaley(1990) and Chan(1992) is adopted in this study. The speed and magnitude of the lead-lag relationship are analyzed using the following formula:

$$R_{IPE,t} = \alpha + \sum_{k=-n}^{n} \beta_k R_{NYMEX,t+k} + \epsilon_t \tag{6.21}$$

where R_{IPE} is the 5-minute interval return series of IPE nearby futures contracts in the afternoon. R_{NYMEX} is the 5-minute interval return series of NYMEX nearby futures contracts. When k < 0, R_{NYMEX} is taken as a lead indicator of R_{IPE}; when k > 0, R_{NYMEX} is taken as a lag indicator of R_{IPE} and when k = 0, β_0 measures the contemporaneous relationship between R_{NYMEX} and R_{IPE}. Significant NYMEX lead coefficients indicate NYMEX return leads have predictive power over current IPE return series, in other words, NYMEX returns lead IPE returns. On the other hand, significant NYMEX lag indicators indicate IPE returns have predictive power over NYMEX, in other words, the speed of information incorporation in IPE is faster than in NYMEX.

As explained in Chapter 3 when all lag indicators are jointly zero, it implies that NYMEX returns do not Granger cause IPE returns. Likewise if all lead coefficients are jointly zero, it implies that IPE returns do not Granger cause NYMEX returns.

This Granger causality hypothesis is tested by setting $\beta_1 = \beta_2 = ... = \beta_n = 0$ and $\beta_{-1} = \beta_{-2} = ... = \beta_{-n} = 0$ and using chi-square critical values with n degrees of freedom.

Having identified the significance of 1 lag in the cross correlation relationship above, lag length $k = 2$ is deemed suitable for the estimation of the lead-lag relationship as set out in Equation 6.21. To correct the biased standard errors due to serial correlations that are identified in Table 6.18 and possible heteroskedasticity that is likely to be present due to various day-to-day trading activities, Newey West (1987) Generalized Method of Moments (GMM) is applied to Equation 6.21. Consistent parameters of lead-lag relationship are displayed in Table 6.20.

There are three significant coefficients in the lead-lag relationship between IPE and NYMEX return series. They are the first order lead, first order lag and the contemporaneous relationship. By far the strongest relationship is the contemporaneous one, captured by the magnitude of β_0, which is 0.5642. This magnitude suggests these two markets are far from mirror images, indicating there are differences in their information incorporation processes. The NYMEX 1 lead coefficient has the magnitude of 0.1812 and NYMEX 1 lag coefficient has the magnitude of 0.0570. Although both coefficients are significant the magnitude of the NYMEX lead is three times that of the lag coefficient. In other words, the predictive power of NYMEX dominates the predictive power of IPE. The hypothesis that all lead coefficients or all lag coefficients are equal to zero is firmly rejected using $\chi^2(2)$ test, further confirming the lead-lag re-

Lead - lag regression analysis on simultaneous trading sessions $R_{IPE,t} = \alpha + \sum_{k=-2}^{2} \beta_k R_{NYMEX,t+k} + \epsilon_t$	
α	-0.000005 (-0.4931)
β_{+2}	0.0036315 (0.5131)
β_{+1}	**0.057048** (5.7493)
β_0	**0.564206** (43.5432)
β_{-1}	**0.181174** (19.3724)
β_{-2}	0.018287 (2.3229)
R^2	0.456547
$\chi^2_{lead}(2)$	**33.12** (ρ=0.00000006)
$\chi^2_{lag}(2)$	**402.94** (ρ= 0.0000000)
Number of observations	12817
Numbers in bold indicate the significance of the coefficients adjusted for serial correlation and heteroskedasticity, significance level is set at 0.001.	

Table 6.20:Lead-lag in 5-minute Return Intervals betwen NYMEX and IPE Afternoon Session

lationship in both directions. The above results from the lead-lag analysis of the IPE on NYMEX indicate information transmission takes place between IPE and NYMEX in both directions in 5 minute intervals with NYMEX's predictive power dominating that of IPE. Tests on lead-lag relationship of NYMEX on IPE are also carried and the above implications remain intact.

6.4.2 News effects

The above section establishes the lead-lag relationship in the simultaneous trading session between IPE and NYMEX. These analyses are based on a pooled data set of 244 days. The results can be regarded as an average lead-lag relationship behaviour in the period of time under investigation. This section aims to test whether this lead-lag relationship holds when major market news arrives. In other words, whether there are any significant changes in the sign, direction or magnitude in the lead-lag relationship when major market events take place. Given the characteristics of IPE and NYMEX we expect different reactions from them as NYMEX is normally regarded as representative of the demand side while IPE is normally regarded as representative of the supply side for crude.

To facilitate this experiment, two types of market news are analyzed. First, the supply side news. Examples of such events include announcements about the adjustment of oil production of major oil exporting countries - eg OPEC. The second type is demand side news which is chosen to be exclusively linked to US domestic oil usage. The reasons for using different types of news effects are as follows. Chapter 2 has analyzed the characteristics of IPE and NYMEX. IPE is regarded as an international market exporting crude oil, while NYMEX is very much a domestic market importing crude oil. With the existence of local demand / supply asymmetry, supply / demand shocks are expected to have different effects, so does the lead-lag relationship.

A total of 7 supply side news events and 6 demand side news events are selected from US Energy Information Administration. Details are listed in Appendix 6.A. Since the news effects are forward looking and the market expectations of the events are often discounted in the prices before the actual arrival of the news, we use two days' data to capture the news effects, a day before the news event together with the day when the event actually takes place. There are 14 days used for supply side news effects analyses and 12 days for demand side news effects. Each type is estimated using Equation 6.21. Results are displayed in Table 6.21.

Several interesting results emerge from the news effects:

(1) contemporaneous relationship between IPE and NYMEX

Return coefficients are stronger (weaker) at 0.635 (0.511) when there is demand (supply) side news. It implies the two markets are more closely linked when there is a major US news release. On the other hand, when there are major supply side news, mainly the OPEC news about their future production, contemporaneous linkage between the two markets becomes weaker. The result is expected as OPEC production changes is an event of global significance. There are other major producers in the oil market and their reaction would also play an important role in the oil price discovery

Lead - lag regression analysis under news effects $R_{IPE,t} = \alpha + \sum_{k=-2}^{2} \beta_k R_{NYMEX,t+k} + \epsilon_t$		
	With supply side news	With demand side news
α	-0.000058 (-0.000050)	0.000017 (0.40994)
β_{+2}	-0.001076 (-0.03133)	0.001022 (0.03734)
β_{+1}	**0.079310** (2.70550)	0.0452291 (1.86668)
β_0	**0.511273** (9.80305)	**0.634838** (19.20415)
β_{-1}	**0.145826** (4.99683)	**0.175871** (6.72304)
β_{-2}	0.059364 (1.87153)	0.03011 (1.20264)
R^2	0.374614	0.520793
$\chi^2_{lead}(2)$	7.5787 (ρ=0.0226)	3.821395 (ρ=0.1479)
$\chi^2_{lag}(2)$	26.0554 (ρ=0.000002)	46.089643 (ρ=0.000000)
Number of observations	696	702
Numbers in bold indicate the significance of the coefficient adjusted for serial correlation and heteroskedasticity. The significance level used in these equations, unlike other tests in this chapter, is the conventional 0.05, due to the reduced number of observations.		

Table 6.21:Lead-lag Relationship in 5-minute Return between NYNEX and IPE afternoon session with News Effects

process, and as a result the link between IPE and NYMEX is comparatively weaker. The increased R bar squared with demand side news and the decreased R bar squared with the supply side news confirms the above finding.

(2) one period lead indicator of IPE

The coefficient of one period lead indicator of IPE is significant and larger in supply-side news but insignificant in demand-side news. It is consistent with our expectation of IPE playing a bigger role in supply side price discovery and NYMEX being more closely linked to the demand side. Furthermore, it is interesting to note that when there are demand side news events, the lead lag relationship is unidirectional, from NYMEX to IPE, not the other way around, which further strengthens the argument that NYMEX is the demand oriented market.

(3) one period lead indicator of NYMEX

Coefficients of NYMEX lead indicators are significant at order one with the magnitude of 0.1458 and 0.1759 for the supply and demand news respectively. The smaller magnitude of supply news indicates that IPE is more efficient in information incorporation when there are major OPEC news events, which further strengthens our expectation of IPE behaviour. In the case of demand-side news, the magnitude of first lag NYMEX predictability remains literally unchanged while in the case of supply-side news, the magnitude is smaller with value of 0.1458. It is consistent with the fact that IPE is more of a supply-oriented market.

6.5 Conclusion

This chapter analyzes 5-minute interval returns of IPE afternoon session and NYMEX to detect the temporal lead-lag relationship between the two futures markets. Results indicate a bidirectional relationship between the two, however the lead of NYMEX futures is dominant within 5-minute intervals. This result is consistent with early indications of NYMEX's lead on the basis of daily observations, as discussed in previous chapters. Further analysis is conducted for the lead-lag relationship under major news effects both on the supply side and demand side with the following conclusions: (1) the two markets move closer when there are major US news events taking place and IPE is more efficient in information incorporation when there are major news events both on the supply and the demand sides; (2) the lead of NYMEX is stronger when there are major US events and that of IPE is stronger when there are major supply side events.

The above conclusions are consistent with our understanding that the IPE-traded Brent contract is a major supply side marker crude while the NYMEX- traded WTI contract is a major demand side marker crude. These results are useful for market participants, in particular for hedgers and traders, who can construct optimal positions under different market conditions. However caution should be exercised when interpreting these results as the sample period and events under investigation are limited.

6.A Appendix

6.A.1 News events on supply side: (source: US Energy Information Administration)

017/01/00 Statoil shuts in 390,000 barrels per day of crude oil production in response to severe weather in the North Sea. Including earlier moves by Norsk Hydro, Statoil, and Shell, a total of 1.27 million barrels per day of North Sea crude oil production is shut due to weather. (DJ)

02/08/00 Russia's second largest oil company, Yukos Oil, announces an agreement with state oil pipeline company Transneft to build a $1.7 billion oil pipeline from Siberia to China. The pipeline would run from Angarsk in Siberia to Beijing. (WSJ)

28/03/00 After two days of meetings, oil ministers of the Organization of Petroleum Exporting Countries (OPEC) agree on an increase in oil production of 1.452 million barrels per day by its members, excluding Iran and Iraq. Iraq, has not been subject to OPEC production agreements while under U.N. Security Council sanctions. Iran, though not formally signing up on to the agreement, stated its intention to raise its production in order to avoid loss of its market share. This would represent about a 1.7 million barrel per day increase in OPEC production targets, if Iran was included. Meanwhile, several major non-OPEC producers, including Mexico and Norway, also have indicated an intention to raise production. (DJ)

21/06/00 Oil ministers from the Organization of Petroleum Exporting Countries (OPEC), meeting in Vienna, agree to raise crude oil production quotas by a total of 708,000 barrels per day. OPEC's total production quota (excluding Iraq) will rise to 25.4 million barrels per day as of July 1, 2000. The next day, crude oil futures rise, with the New York Mercantile Exchange (NYMEX) August West Texas Intermediate contract closing June 22 at $32.19.

29/06/00 Norway's Oil and Energy ministry announces that it is rescinding its production cut of 100,000 barrels per day, which it had undertaken in cooperation with production cuts by the Organization of Petroleum Exporting Countries (OPEC), of which it is not a member.

01/08/00 The Organization of Petroleum Exporting Countries (OPEC) officially tells member governments to cancel plans to raise production.

30/10/00 The president of the Organization of Petroleum Exporting Countries (OPEC), Venezuelan oil minister Ali Rodriguez, announces that the cartel will raise production quotas by 500,000 barrels per day, beginning November 1st. OPEC's action comes as a result of its "price band" mechanism, which triggers an increase in production quotas when the price of the OPEC basket of crude oils closes over $28 per barrel for twenty consecutive trading days. Many analysts voice doubt as to whether the OPEC quota increase will lead to an actual increase in production of that magnitude, given the lack of spare production capacity of most OPEC members. (DJ, WP, WSJ)

6.A.2 US based news events on demand side (source: US Energy

Information Administration)

27-Jan-00 Senator Charles Schumer meets with Secretary of Energy Bill Richardson to press for a sale of oil from the Strategic Petroleum Reserve (SPR) in response to high oil prices. In particular, northeastern members of Congress have been concerned by the sharp rise in prices for heating oil in late January 2000 due to cold temperatures on the East Coast of the United States. (DJ)

16-May-00 Senate majority leader Trent Lott and other Republicans introduce legislation intended to boost United States domestic oil production. Among other actions, the bill would provide a tax credit of up to $3 per barrel for production from marginal wells during periods of low oil prices and open up the coastal portion of the Arctic National Wildlife Refuge (ANWR) to oil exploration. (DJ)

15-Jun-00 The Department of Energy orders the release of 500,000 barrels of crude oil from the Strategic Petroleum Reserve (SPR). The oil is to be loaned to Citgo's refinery at Lake Charles, Louisiana, which has been cut off from its normal crude oil supplies by an obstructed waterway. (DJ)

23-Aug-00 The Energy Information Administration reports that crude oil stock levels in the United States have fallen to their lowest level since 1976. Crude oil for October delivery closes at $32.02 on the New York Mercantile Exchange (NYMEX), up 80 cents. (DJ)

22-Sep-00 President Clinton authorizes the release of 30 million barrels of oil from the Strategic Petroleum Reserve (SPR) over 30 days to bolster oil supplies, particularly heating oil in the Northeast. The release will take the form of a "swap," in which crude oil volumes drawn from the SPR will be replaced by the recipients at a later date. Crude oil for November delivery falls four percent, to $32.68, on the New York Mercantile Exchange (NYMEX). (DJ)

30-Nov-00 Natural gas futures soar to a record high as forecasts for colder weather in the Northeast and Midwest threaten to boost demand at a time when supplies of natural gas in storage are at low levels. Natural gas closes at $6.59 per million British thermal units on the New York Mercantile Exchange (NYMEX), a rise of 40.8 cents.(DJ)

Chapter 7
Duration Analysis

7.1 Introduction

So far in this thesis the relationship between IPE morning trading session and NYMEX trading session has been modeled on a daily and half-daily basis with univariate and multivariate time series analysis in Chapters 4 and 5 respectively. Temporal relationships between IPE afternoon and NYMEX trading sessions are captured in Chapter 6 using 5-minute interval return analyses. Up till now IPE morning and afternoon trading sessions have been separated artificially and examined individually using different time frequency data. In this chapter trading activities of IPE are to be investigated as a whole in order to give a consistent view of the IPE information incorporation system. As explained earlier, due to the high speed nature of information transmission, high frequency analysis is desirable. Trade durations, i.e. the time between transactions, serve well as a vehicle to carry out a coherent intra-day analysis of IPE. Effects of NYMEX trading on the IPE are expected to have a strong impact on IPE trading characteristics within a day. To our knowledge this is the first attempt to apply this method in the area of energy futures markets.

Engle & Russell's (1998) Autoregressive Conditional Duration (ACD) analysis methodology is applied in this chapter. Duration analysis has existed for a long time in the form of survival studies in engineering and medicine. It is introduced in economics for the first time by Lancaster (1972, 1979) to analyze spells of unemployment and strikes. Recently, duration analysis is applied in finance by Engle and Russell (1998) using tick-by-tick transaction data. Just as time spans between jobs are treated as a random variable in Lancaster's model, so is the time duration between trades in Engle and Russell. This duration concept is in direct contrast to the use of fixed interval observations in conventional econometric methodologies. Familiar fixed clock time interval analysis no longer applies as trade durations are likely to be different from one another. Duration data are the rawest data set that one can get and it contains extra information over and above those enclosed in fixed interval data. For example, when markets are busy, a lot of events are happening and time between events flows at a faster pace. On the other hand, when markets are quiet, not many events are occurring and time between events flows slower. Within a fixed interval framework detailed transaction information is discarded because of aggregation. Such aggregation has the danger of either introducing false autocorrelation when there aren't any events in the time interval, or throwing away important market information when there are a lot of events happening within an interval. Therefore the analysis of trade durations of IPE are expected to uncover more information on trading activities than conventional fixed interval analysis and should be a better methodology than the conventional methodology for the purpose of this investigation.

The rest of the chapter is organized as follows: Section 7.2 introduces Engle and Russell's (1998) ACD model, its application and development so far. Section 7.3 discusses the data construction process, its advantages, disavantages and properties of the resultant data. Section 7.4 applies the simple version of ACD model and presents empirical results and their implications. Finally, conclusions and further research directions are discussed in Section 7.5.

7.2 Literature review

Engle and Russell (1998) introduce the ACD model and test it using transaction data of the IBM stock trade on NYSE. Trade duration in their model is defined as the length of time between two trades. This model analyzes the raw data set - transaction by transaction data, where no aggregations have taken place. This form of data provides new information on different states of markets to which we did not have access before, in particular the "flow of time" concept. When markets are busy, a lot of events are happening, gaps between two events are small, in other words transaction time flows at a faster speed and the information revealing process also speeds up. On the other hand, when markets are quiet, not many events are happening and transaction time flows more slowly and the information revealing process also moves at a slower pace. Analyzing and modelling the tick by tick transaction data helps market participants to uncover market information, such as liquidity, and to adopt appropriate strategies, such as choosing a suitable market state and time to enter or exit.

Empirical observation demonstrates a strong pattern of duration clustering; a short duration tends to follow another short duration while a long duration tends to follow another long duration. Two possible explanations have been put forward for the observed duration clustering: (1) trader's strategic behaviour, and (2) liquidity issues. Both explanations are discussed below:

Trader's strategic behaviour

There are three categories of participants in a market: liquidity traders, informed traders and market makers. Liquidity traders have no private information, they trade for liquidity while informed traders have private information, they trade to make a profit through their private information. Market makers quote bid-ask spreads to any potential buyers and sellers.

Easley and O'Hara (1992) make the common assumption that liquidity traders arrive randomly according to a Poisson distribution. Informed traders, will enter the market only after observing a private, potentially noisy signal. In a rational expectations setting the specialist or the market maker knows this and will slowly learn of the private information by watching order flow and hence adjust prices accordingly. Informed traders will seek to trade as long as their information has value. Hence, we should see clustering of trading following an information event due to an increased number of informed traders. Admati and Pfleiderer (1988) develop a model where, in addition to informed traders, there are two further uninformed liquidity traders: the "discretionary traders" and the "non-discretionary traders". The "discretionary" liquidity traders have some choice over the time at which they transact while the "non-discretionary" liquidity traders are again assumed to arrive in a random fashion. Since the bid-ask spread in the model is inversely related to the discretionary trader volume, it is optimal for discretionary liquidity traders to lump their trades together in the same batch auction. The informed traders would also choose to trade at this time but the number of informed traders is exogenous so the increases in volume are associated with increased number of liquidity traders. As explained from the above, strategic behaviours would and do contribute to the autocorrelation of the durations as well as influence the trading volume.

Liquidity issues

On the other hand, the market liquidity condition also influences the behaviour of traders. Market liquidity is a dynamic concept: it is defined as the maximum amount of transactions that one can trade without moving the prevailing price, or in other words, the ability to trade costlessly. Liquid markets are generally regarded as those which accommodate trades with the least effect on price. Applied measures of liquidity take several forms, explained subsequently.

1. order flow as in Kyle's model with larger order flow as regarded as a characteristic of a more liquid market.

2. bid-ask spread, with liquid markets having small spreads;

3. price of immediacy as in Grossman and Miller's (1988) model (See p 217 of O'Hara(1995)), where it is explained that the number of speculators determines how much of the underlying private information and hence market liquidity there is within a point in time.

4. "price duration" introduced by Engle and Russell (1998), as the time between two trades when certain predetermined price changes occur, which has the desirable property for measuring market liquidity. This "price duration" concept is further applied to measure the market depth in Engle and Lange's (2001) paper, by linking it to the volatility of the market. The expected length of a price duration is inversely proportional to the expected volatility. The higher the price duration, the longer the gap between two price changes and more liquid the market.

A potential strategy of liquidity traders would be to minimize trading cost by entering the market when it is most liquid. They can achieve this by using the following indicators. Firstly, volume; the higher the volume, the more liquid the market, so that liquidity traders would choose a higher-volume market to trade. Secondly, price duration; the shorter the price duration, the less liquid the market is. A liquidity trader would avoid the less liquid moments. This supports the idea that market liquidity reduces when it is flooded by informed traders. Liquidity traders should avoid trading under this kind of market condition as the probability of losing to informed traders is high.

7.2.1 ACD model

After the discussion of the causes and effects of the market durations to the behaviour of various strategic traders, we introduce the ACD model. Engle and Russell's highly influential ACD is designed to model the dynamic effects of the duration between transactions. This clustering effect is very similar to observed volatility clustering as described in ARCH / GARCH type of models. Specifically the conditional duration is a linear function of past durations and past events. Duration is the time gap between two transactions. The ACD model is set up as follows. ψ is defined as the expectation of the duration.

$$E_{i-1}(x_i|x_{i-1,\ldots,}x_1) = \psi_i(x_{i-1,\ldots,}x_{1;}\theta) \equiv \psi_i \tag{7.22}$$

where actual duration $x_i = t_i - t_{i-1}$ The expected duration follows an autoregressive process and specifically catches an empirical observation of the duration clustering effect: short durations tend to follow short durations while long durations tend to follow long durations.

$$\psi_i = w + \sum_{j=0}^{p} \alpha_j x_{i-j} + \sum_{k=0}^{q} \beta_k \psi_{i-k} \tag{7.23}$$

The ACD class of models consists of parameters p and q and the following assumption:

$$x_i \equiv \psi_i * \varepsilon_i \tag{7.24}$$

where $\{\varepsilon_i\} \sim$ iid with probability distribution function $\rho(\varepsilon; \Phi)$ and parameter Φ, and θ in Equation 7.22, are variation free.

Various forms of distribution can be taken in ε_i, Engle and Russell in their paper use the exponential and Weibull distributions on the analysis of trade durations, price durations and market microstructure hypotheses. For simplicity as well as due to data restrictions, only the exponential distribution is applied in this chapter.

7.2.2 Extension of ACD model

After the seminal work on the ACD model by Engle and Russell, several research papers have tried to extend the model. One such direction is to adopt different distributions for the underlying data generating process. For example, as an alternative to exponential and Weibull distributions, Gramming and Maurer (1999) introduce an ACD model based on the Burr distribution.

The other line of the extension of ACD is to improve the structure alteration of the original ACD. One of the implied restrictions on the ACD model is the non-negativity imposed on the coefficient of the autoregressive term as in α and β in Equation7.23. Bauwens and Giot (1997) proposed the logarithmic ACD model where the autoregressive equation is specified on the logarithm of the conditional expectation of the durations. This model is free from the non-negativity restriction and therefore more flexible than the ACD model. They applied this model on the bid-ask quote process of three very actively traded securities: US Robotics of NASDAQ and IBM of NYSE, and found that the bid-ask quote durations exhibit a highly autoregressive structure and that these durations are closely related to liquidity.

Jasiak (1996) uses the fractionally integrated ACD model which accommodates a long memory process in the duration. GARCH-ACD by Ghysels and Jasiak (1997) is also called random coefficient GARCH, or doubly stochastic GARCH. It is a truly bivariate process where past asset return volatilities are allowed to affect transaction durations and vice versa. This bivariate setting enables the testing of Granger Causality between volatility and intra-trade durations. The author tests this method on IBM stock and finds the persistence in GARCH drops dramatically once intra-trade durations are taken into account.

ACD models are still in the development stage; many of their properties, eg higher moments, are unknown to researchers. Estimation can also be difficult. They provide the challenge for future research, however, caution must be exercised when results from these models are utilized.

7.3 Data

In this chapter, the tick by tick database from IPE is utilized. Only trade data are analyzed. Each trade quote is time stamped to the second. A trade duration is taken as the time length between two transactions. Data start from 14th April 2000 when the June contract assumes its first position and finishes on 16th May 2000 when the contract expires. The advantage of choosing this data set is that they are now free of

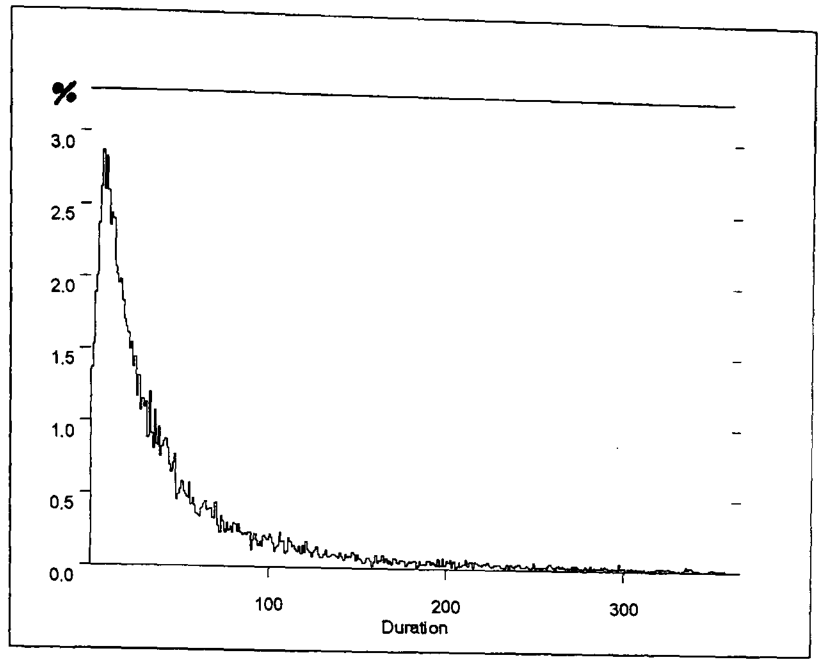

Figure 7.6: Histogram of raw durations (seconds)

jumps of basis risk caused by using different futures contracts. The total number of observations is 13,856. A histogram of raw durations is displayed in Figure 7.6. High frequency exists in short durations and then sharply deteriorates to long durations.

The minimum duration between events in the data set is a fraction of the second. There are fourteen such occasions. The maximum time interval between trades happens at 13:56 of 12th May when the duration stands at 3723 seconds or 62 minutes. The average waiting time (excluding overnight closure) between trades is 54.5 seconds and standard deviation is 98.5 seconds.

As discussed earlier, IPE starts trading at 10:02 GMT and ends trading at 20:13 GMT. The first month contract starts to trade at 10:02 for a minute, then the second month opens to trade while the first month contract continues to trade, and so on and so forth until five near contracts are all trading at the end of 10:06. The opening price of each contact is calculated as the average of the first minute trading prices. As opening prices are expected to be heavily influenced by the overnight information which has not had an opportunity to be incorporated in prices, observations in first minute trading are deleted to avoid the contamination of overnight information. The average duration of the next 3-minute trading is used as the conditional duration for the first observation of the day, in other words, analysis starts from 10:10am. With this structure we also avoid carrying over the transaction rate of the previous close to the next opening. Details of daily conditional opening durations are listed in Appendix 7.A. The total sample size is 13,388 after the adjustment to the opening data.

7.3.1 Data descriptive analysis

Column 1 of Table 7.22 and Figure 7.7 display the autocorrelation functions for the raw durations. The values are far from zero. Ljung-Box tests for null hypothesis of no-autocorrelation for the first 15 lags firmly reject it at 5511[6].

7.3.2 Diurnal pattern

Figure 7.8 shows the diurnal factor of IPE trade durations. A knot is placed on each one hour and 1/2 hour of the trading day and a smooth spline is produced with the knots,

6 Due to large sample significance level is adjusted to 0.001 according to Lindley throughout the chapter.

Order	Autocorrelation before deseasonalization	Autocorrelation after deseasonalization
1	0.2331	0.193603
2	0.2110	0.167267
3	0.1834	0.150143
4	0.1898	0.154306
5	0.2035	0.141158
6	0.1844	0.123701
7	0.1517	0.133879
8	0.1487	0.124948
9	0.1499	0.1124
10	0.1206	0.08997
11	0.1411	0.115525
12	0.1402	0.111492
13	0.1286	0.109284
14	0.1257	0.118326
15	0.1164	0.104734
	Ljung-Box (15) = 5511	Ljung-Box (15) = 3535

Table 7.22:Autocorrelation Function of the duration before and after deseasonalized

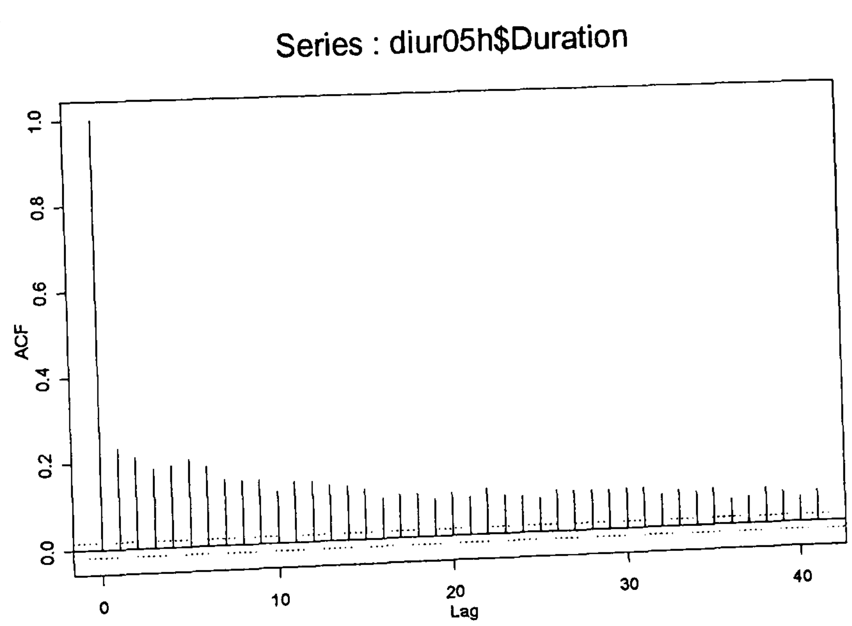

Figure 7.7: Autocorrelation functions of raw durations

using S-plus. This diurnal pattern is treated as "intra-day seasonality" equivalent to seasonality in quarterly or yearly data.

Different behaviours are expected from IPE morning and afternoon sections due to the trading of NYMEX. Empirical work often produces the inverted U-shape of duration pattern within a day. This pattern is repeated in the trade duration graph of this data set. In addition, it has two unique features: (1) Two inverted U-shape patterns are distinguishable: one from the opening till 14:45, which we call the "morning U"; the other from 14:45 till close, which we call the "afternoon U". (2) The "morning U" can be described as a leptokurtic inverted U-shaped curve while the afternoon is a platykurtic inverted U-shaped curve. The "morning U" starts with a short duration of 37 seconds between trades and reaches its peak at 1:30pm with 251 seconds on average for a trade to take place, then drops back at 2:45pm when NYMEX starts to trade. The point in time that NYMEX starts to trade also serves as the starting point of the IPE afternoon session with an average waiting time between trades of 53 seconds. Durations between transactions increase gradually, with the peak at 6pm of one transaction every 131 seconds. At the closing, average duration between trades drops back to 49 seconds.

Since durations are expected to convey information, the distinctive difference in trading behaviour in duration between IPE morning and afternoon sections implies that information is more ample in the IPE afternoon session, which in term suggests NYMEX trading has a dominant intra-day seasonality effect on trades of IPE.

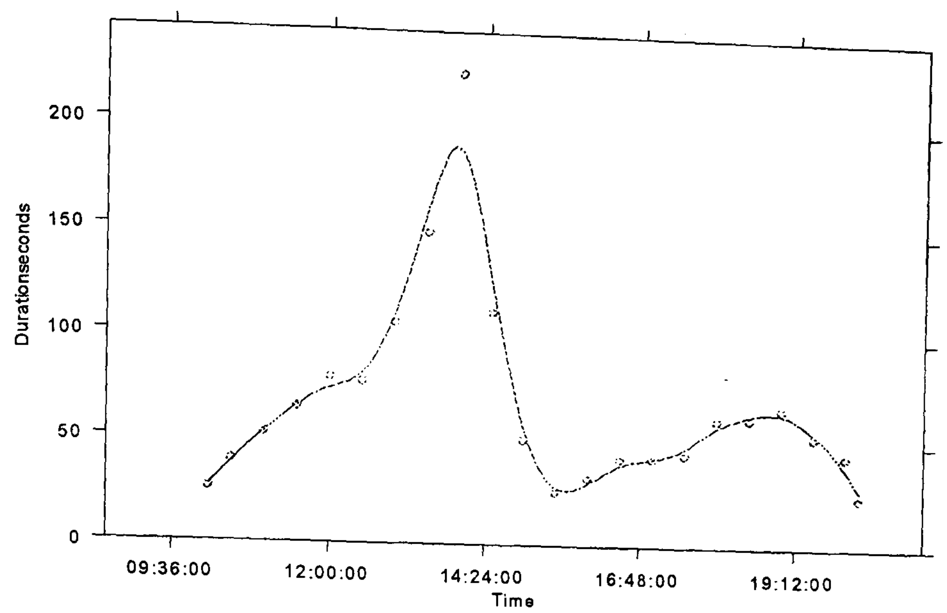

Figure 7.8: Diurnal Factor of IPE Trading Hours

Next, deseasonalisation, or the removal of diurnal factor, is carried out on trade duration data and an ACD model is applied to uncover the trading behaviour of IPE. The formula for deseasonalisation is as follows:

$$\hat{x}_{i-1} \equiv \frac{x_{i-1}}{\phi(t_{i-1})}$$

The deseasonalized duration is the actual duration scaled by the diurnal factor.

Two graphs, Figure 7.9 and Figure 7.10, demonstrate the effects of deseasonalization. Figure 7.9 is the scattered plot of raw durations before deseasonalization and Figure 7.10 is the scattered plot of deseasonalized durations.

Column 2 of Table 7.22 and Figure 7.11 display the autocorrelation of durations after the extraction of diurnal factors. De-seasonalization reduces the magnitudes of

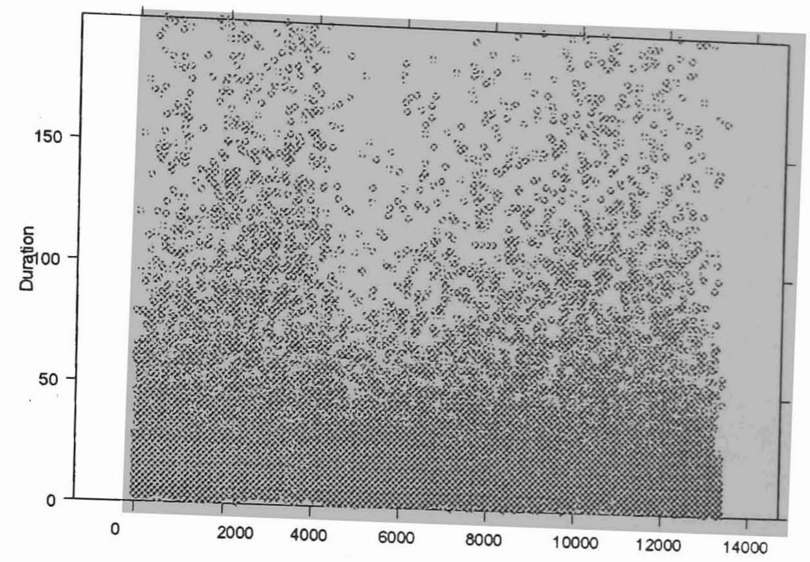

Figure 7.9: Scatterplot for Raw Durations

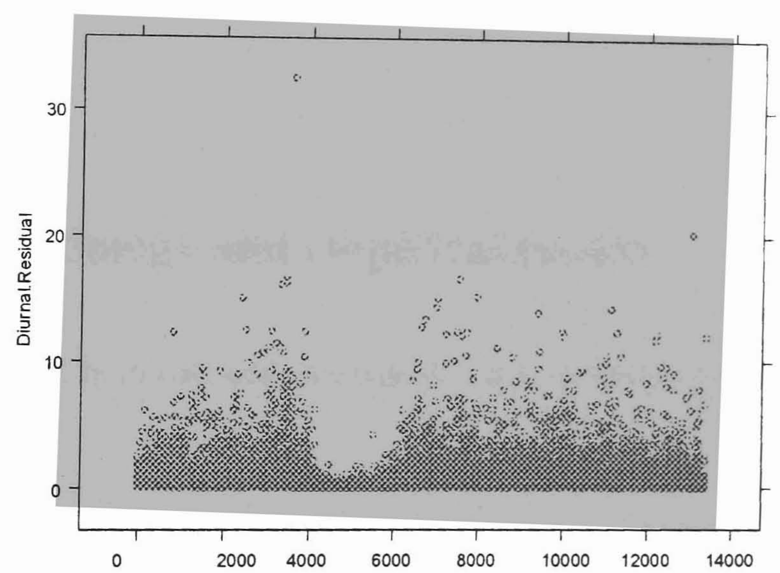

Figure 7.10: Scatter Plot: Deseasonalized Durations

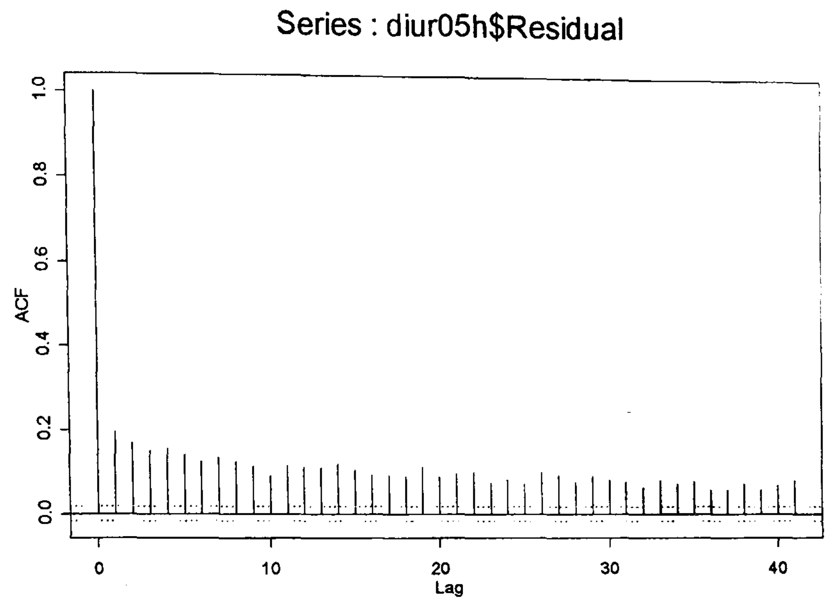

Figure 7.11: Autocorrelation Function of Durations After the Removal of Diurnal Factors

autocorrelation coefficients across the broad. However the pattern of ACF remains. ACD model is applied to the deseasonalized data series.

7.4 Methodology and empirical results

After ACD model is introduced in Section 7.2.1, a simple version is applied in this chapter.

7.4.1 A simple version of ACD model

A simple version of ACD model of Equation (7.23) is an exponential ACD(1,1) set out as follows:

$$E_{i-1}(x_i) \equiv \psi_i = w + \alpha x_{i-1} + \beta \psi_{i-1} \tag{7.25}$$

$$x_i \equiv \psi_i * \varepsilon_i \tag{7.26}$$

$\{\varepsilon_i\}$ ~i.i.d. exponential $f(\lambda)$, with its parameter λ and (w, α, β) are variation free, $x_i = t_i - t_{i-1}$ is the interval between two events, called duration, t_i is the time when event i takes place, ψ_i is the expected ith duration, ε_i is the residual.

This version of EACD(1,1) model is to be used in duration analysis in IPE crude oil futures contacts. It is also used in Engle and Russell's paper in analyzing IBM data. In this model the expected duration is affected by its past one period events. The actual duration is the result of the expected duration combined with an error term. It is chosen due to its special property of QMLE estimation, which will be discussed below. The simplicity of the EACD(1,1) model lies in the use of a multiplicative error and its connection to the established QMLE properties of the GARCH(1,1). Using Lee and Hansen's (1994) theorems or Lumsdaine's (1996) theorems, Engle and Russel prove the deeper connection between GARCH(1,1) model and ACD(1,1) model.

Corollary to Lee and Hansen (1994): if:

A $E_{i-1}(x_i) \equiv \psi_{0,i} = \omega + \alpha_0 x_{i-1} + \beta_0 \psi_{0,i-1}$;

B $\varepsilon_i \equiv x_i / \psi_{0,i}$ is (i) strictly stationary and ergodic, (ii) nondegenerate, (iii) has bounded conditional second moments, (iv) $sup_i E[ln(\beta_0 + \alpha_0 \epsilon_i) | F_{i-1}] < 0$ a.s. ;

C $\theta_0 \equiv (\omega_0, \alpha_0, \beta_0)$ is the interior of Θ;

D $L(\Theta) = -\sum_{i=1}^{N(T)} \{\log(\psi_i) + \frac{x_i}{\psi_i}\}$ where $\psi_i = \omega + \alpha x_i + \beta\psi_{i-1}$ for $i > 1$, $\psi_i = \omega/(1-\beta)$ for $i = 1$;

then:

a the maximizer of L will be consistent and asymptotically normal with a covariance matrix given by the familiar robust standard errors from Lee-Hansen: and

b the model can be estimated with ARCH software by taking $\sqrt{x_i}$ as the dependent variable and setting the mean to zero

$$L(\Theta) = -\sum_{i=1}^{N(T)} \{\log(\psi_i) + \frac{x_i}{\psi_i}\} \tag{7.27}$$

The beauty of using the EACD(1,1) quasi maximum likelihood estimation method is that without exact prior knowledge about the empirical distribution of data one can forecast the empirical distribution as the exponential, then use the QMLE estimation to derive a consistent, though not necessary efficient, estimation of parameters. In addition, the established QMLE properties of GARCH, even in the presence of unit roots, can be carried over to EACD(1,1).

After the estimation, the empirical distribution of the data can be checked against the hypothesized exponential distribution. If the mean and standard deviation are equal, then the empirical distribution of the data is indeed exponential and the ACD model fits the underlying data distribution well. However, if the mean and standard deviation are not equal then the underlying data generating function is not exponential. But the estimated parameters are still consistent and valid due to the QMLE property.

In this simple EACD(1,1) model, the unconditional mean is given by

$$E(x_j) = \mu = \frac{\omega}{(1-\Sigma(\alpha_j+\beta_i))}$$

and the unconditional variance is given by

$\sigma^2 = \mu^2 \left(\frac{1-\beta^2-2\alpha\beta}{1-\beta^2-2\alpha\beta-2\alpha^2}\right)$ When the unconditional standard deviation exceeds the unconditional mean, it is called **excess dispersion**. It happens whenever $\alpha > 0$.

Despite the simplicity and consistency of the parameter estimation through QMLE, the EACD(1,1) has its own weak point. The modelling process is concentrated on the conditional first moment, ignoring other moments. This criticism can potentially produce biased estimation if the higher moments have a large role to play in the process therefore when results are interpreted, caution must be exercised.

EACD(1,1) model, is applied to the duration data after the adjustments of diurnal factor, firstly to the entire trading activity; then with dummy variables for the afternoon session to catch any possible different trading behaviour from the effects of NYMEX

Variable	Coefficient	Std Error	T-statistics
c	0.0320	0.0026	12.5188
a	0.1192	0.0043	27.6472
b	0.8507	0.0051	167.1687
Residual statistics Ljung-Box Q(15) 28.7814. (Significance Level) 0.0171 mean 1.0021 Std Error 1.2253			
Notes: $E_{i-1}(x_i) \equiv \psi_i = c + a\hat{x}_{i-1} + b\psi_{i-1}$ where $\hat{x}_{i-1} \equiv \frac{x_{i-1}}{\phi(t_{i-1})}$, deseasonalized duration			
Note: Significance level used for statistics tests is at 0.001.			

Table 7.23:ACD Model with All Observations

trading. The Berndt, Hall, Hall, Hausmann (1974) algorithm is applied to maximize the likelihood.

The estimation results using all observations and with dummy variables are displayed in tables 7.23 and 7.24 respectively.

In table 7.23 parameter estimates of the conditional duration model are all highly significant. The sum of the coefficients of the autoregressive duration a and b is 0.97, indicating the highly persistent nature of the duration. News arrival during a day has lasting effects. Although the magnitude is close to 1, the property of the Engle and Russell's EACD(1,1) model ensures that the inference is valid. The mean of the transaction is very close to 1 and the standard deviation is 1.22, which indicates that excess dispersion is present. The departure of the residual mean from the standard deviation indicates that the distribution is not exponential and this result is expected. However, the estimation results are again consistent under the QMLE condition. The Ljung-Box(15) test on the residual is 28.78, insignificant (the critical value is 37.7 at 0.001 level), which implies the residuals in the ACD model are now free from serial corre-

$E_{i-1}(x_i) \equiv \psi_i = c + d_1 + a\psi_{i-1} + d_2\psi_{i-1} + bx_{i-1} + d_3x_{i-1}$								
EACD(1,1) morning				EACD(1,1) afternoon Dummy for IPE afternoon				Combined Effects
Parameter	Coefficient	Std Error	T - Statistics		Coefficient	Std Error	T - Statistics	Coefficient
c	**0.0735**	0.0077	9.4973	d1	-0.0531	0.0081	6.5387	0.0204
a	0.1670	0.0106	15.8213	d2	-0.0653	0.0116	5.6269	0.1017
b	0.7687	0.0134	57.2782	d3	0.1099	0.0145	7.5873	0.8786
Residual statistics Ljung Box Q(15) 23.4724, (Significance Level) 0.07461278 Mean 1.0005 Standard Error 1.2192								
Note: Significance level used for statistics tests is at 0.001.								

Table 7.24:Estimated ACD model with IPE Morning / Afternoon Data

lation. It is a big improvement when compared to the raw durations. The ACD model performs well for the current transaction data compared with the raw data.

Next, estimation on IPE morning and afternoon sessions is conducted by including dummy variables in the afternoon to catch any possible significant different trading behaviours. To accommodate the estimation, duration data are divided into two sections with the opening of NYMEX as the dividing point. There are 4142 observations of trades in the morning session before NYMEX opens and 9246 observations of trades in the afternoon session. The fact that the number of transactions in the afternoon session is twice as much as those in the morning predicts the shorter average duration in the afternoon. This is confirmed by the diurnal factor shown in Figure ??. EACD(1,1) results with three dummy variables on constant and two other parameters are shown in Table 7.24.

The significant coefficients of all dummy variables indicate that EACD coefficients for IPE morning and afternoon sessions are significantly different from each other, confirming different market behaviours. In particular, the following results can be drawn from the estimation: (a) the mean of the duration is reduced in the afternoon: the constant term in the morning session is much larger than in the afternoon; (b) the persistence of afternoon session is increased as the sum of the coefficient a and b has increased from 0.93 of the morning session to 0.98 of the afternoon session; (c) the individual coefficients of a and b in the ACD model have different magnitudes, indicating different patterns of behaviour in the two trading sessions. (d) although having the wrong underlying distribution the ACD model fits both morning and afternoon data pretty well as indicated by the greatly improved serial correlation statistics in the residuals - the Ljung-Box Q test for autocorrelation of the residuals are insignificant for both morning and afternoon sessions.

The above distinctive behaviours of the IPE morning and afternoon sessions could be explained as follows: (1) News effects: as explained in Chapter 6 different sources of news have significant impact on the prices of futures contracts on the two exchanges. Given NYMEX is the demand side centre, its opening for trading may add new information. (2) Liquidity effects: existing information on both exchange futures contracts demonstrates that NYMEX trading volume is about twice as much as that in IPE, which results in more liquidity in NYMEX. Therefore liquidity traders would have NYMEX as the first choice to trade in (most large participants in the market have access to trading in both exchanges).

The above empirical evidence indicates that ACD model is a good candidate for fitting the observed high frequency tick-by-tick duration data. Of course caution should be exercised when utilizing the above results in devising practical trading rules as the modeling is solely based on the first moment of the data series.

7.5 Conclusion

This chapter builds on the high frequency information transmission mechanism between IPE and NYMEX, with the opening of NYMEX trading providing the focal point. This time we concentrate on the intra-day behaviour of IPE prices and more specifically on trade durations. Intra-day seasonality is extracted and two distinctive trading patterns are displayed for IPE morning and afternoon. Empirical evidence from ACD model also suggests that the patterns of IPE morning and afternoon durations are distinctively different from each other. These findings suggest that NYMEX has a large impact on IPE trading, which is also the conclusion of previous chapters. Whether this impact is the result of information disclosure, such as demand information, or simply due to the trade generated impact is an interesting topic for further study.

7.A Appendix

7.A.1 Detailed knots placed on each half hour of IPE trading hour:

10:06 10:30 11:00 11:30 12:00 12:30 13:00 13:30 14:00 14:30 15:00 15:30 16:00 16:30 17:00 17:30 18:00 18:30 19:00 19:30 20:00 20:13

7.A.2 Conditional duration for the opening of morning and afternoon sessions of June 2000 contract

Date	Starting Duration for morning	Starting Duration for afternoon
17-Apr-2000	29.25	23.50
18-Apr-2000	12.67	41.67
19-Apr-2000	15.08	26.25
20-Apr-2000	54.00	11.00
25-Apr-2000	116.00	29.00
26-Apr-2000	28.00	36.50
27-Apr-2000	13.45	27.00
28-Apr-2000	18.40	22.00
02-May-2000	11.72	25.00
03-May-2000	12.47	47.00
04-May-2000	14.20	55.00
05-May-2000	28.00	12.00
08-May-2000	55.00	80.50
09-May-2000	19.55	34.00
10-May-2000	24.33	42.00
11-May-2000	21.78	144.00
12-May-2000	29.00	79.00
15-May-2000	108.00	152.00
16-May-2000	54.00	143.50

Chapter 8
Conclusion

This thesis is an empirical work focusing on the two dominant world oil price discovering processes - NYMEX and IPE - in order to uncover the speed of information transmission between them and the potential market leader.

The dominant price discovery role played by NYMEX and IPE in the world oil market as well as the theoretical and trading linkages between the two are discussed and established in Chapter 2. This chapter sets the theoretical grounding for empirical research in later chapters. To our knowledge, this is the first attempt to conduct such empirical work on the relationship between the two markets.

To carry out this empirical investigation, various methodologies are applied. Chapter 4 examines the information transmission mechanism between NYMEX and IPE crude oil contracts in a univariate framework using daily data under both overlapping and non-overlapping trading hours. It depicts general characteristics of the interaction between the two markets and it is decided that overlapping trading hours and non-overlapping trading hours should be examined separately. Chapter 5 further investigates the non-overlapping trading hours between IPE and NYMEX with extended observations in a multivariate setting, which takes into account possible interactions between the two markets. Chapter 6 examines 5-minute interval lead-lag relationships between the two markets, using one of the lead-lag methodologies reviewed in Chapter 3. Chapter 7 examines the intra-day behaviour of IPE prices with the NYMEX opening as the focal point. It is achieved by applying an ACD model with tick-by-tick transaction data from IPE. High frequency analysis applied in Chapters 6 and 7 are distinctive innovations in energy futures research, and thus a contribution of this thesis.

8.1 Empirical findings

Non-simultaneous trading sessions of IPE (IPE morning session) and NYMEX are examined in Chapters 4 and 5 with univariate and multivariate time series analysis respectively. In univariate analysis, spillover effects in mean returns are found in the IPE morning session from previous day NYMEX trading information, while no information transmission is found from IPE morning session to NYMEX same-day trading. In multivariate time series analysis with a larger data set, estimation using all data available suggests different results from those using univariate analysis in Chapter 4. However, closer analysis on sub-period estimation reveals results that are consistent with those from Chapter 4: the results from the first sub-period, which has the same observation data as in the univariate analysis, mirror the results from Chapter 4; those from the second sub-period which are extended data have a largely different behaviour from the first sub-period. It thus can be implied that the estimated results using all available information are averages of the behaviour of the two sub-periods. This changing behaviour from one sub-period to the next points to a possible structural break between the two sub-periods. Given that there are no significant political forces, such as "oil shocks", taking place during the period under investigation, the changing forces must be coming from the markets themselves, e.g. IPE opening prices have more efficient in information incorporation in the recent time period. It is an interesting topic but beyond the scope of this thesis.

The simultaneous trading session of IPE (IPE afternoon) and NYMEX is examined in Chapter 6 with 5-minute interval returns of IPE afternoon session and NYMEX to detect the temporal lead-lag relationship between the two futures markets. Results indicate a bidirectional relationship between the two, however the lead of NYMEX futures is dominant within 5-minute intervals. This result is consistent with early indications of NYMEX's lead on the basis of daily observations. Further analysis is conducted for the lead-lag relationship under major news effects both on the supply side and demand side with the following conclusions: (1) the two markets move closer when there are major US news events taking place, and IPE is more efficient in information incorporation when there are major news events both on the supply and the demand sides; (2) the lead of NYMEX is stronger when there are major US events and that of IPE is stronger when there are major supply side events. These findings are consistent with our understanding that the IPE-traded Brent contract is a major supply side marker crude while the NYMEX- traded WTI contract is a major demand side marker crude. These results are useful for market participants, in particular for hedgers and traders, who can construct optimal positions under different market conditions.

After examining the IPE markets as morning and afternoon sessions separately, Chapter 7 scrutinizes IPE intra-day trading behaviour as a whole, with NYMEX opening as the focal point. Empirical evidence from diurnal factor (intra-day seasonality), and from ACD model suggests that the patterns of IPE morning and afternoon durations are distinctively different from each other. These findings suggest that NYMEX has a large impact on IPE trading. Whether this impact is the result of information disclosure, such as demand information, or simply due to the trade generated impact is an interesting topic for further study, if and when necessary data become available.

Empirical findings from previous chapters with various methodologies and frequency of data have been interesting and consistent. In daily data analysis, there are indications of NYMEX lead in non-overlapping trading hours, however this lead is reducing in recent years, implying the increasing independence of the price discovery process of IPE morning session. In the 5-minute interval intra-day analysis, the temporal lead-lag relationships between the two markets are dominant, with NYMEX (5-minute) lead indicator having a larger magnitude; however, this magnitude changes under major different news effects. Finally, the opening of NYMEX has significant effects on the trading of IPE, hence IPE morning and afternoon sessions are distinctively different from each other.

8.2 Implications of findings

Findings in this thesis imply that NYMEX is a leader in the information incorporation process, which is consistent with that obtained for the volatility processes by Brunetti, and Gilbert (2001). But the extent of this leadership changes dynamically: under different news effects, as analyzed in Chapter 6; under different time periods, as discussed in Chapter 5. These findings would impose significant challenges to regulators, in today's global market, to keep their market competitive as well as prudent. They should also benefit hedgers, who after taking into account their hedging implementation criteria such as liquidity, may be able to benefit from the faster information transmission ability of the leading market by directly taking hedging positions using the leading market contracts. The users most likely to benefit from the above findings are traders, who may be able to take arbitrage profits after taking into account trading costs, borrowing costs, etc.

However, a word of caution: empirical findings in this thesis are derived through specific methodologies, during specific time periods using specific data frequencies; any changes in methodologies, time estimation period or data frequency may change the results obtained. Caution should be exercised when applying any of the findings.

8.3 Directions for further research

This thesis also identifies two broad directions for future research.

1. Analyses in this thesis have concentrated on the first moment of data series to provide a consistent view on information transmission between the two markets across different time periods and different data frequencies. The use of second or higher moments is a step forward in the high frequency data analysis, from the methodological point of view.

2. This thesis identifies the leader in a fast changing environment. The causes of the observed findings can be conducted by the comparative studies of the two markets. It is useful to pinpoint what are the "winning factors" and "losing factors" that make or break a market leader, and thus particularly benefitial to regulators and policy makers. Among a large list of factors that maybe included in this study, "liquidity effects" would be an interesting one. As mentioned in Chapter 7 it could be an underlying factor that influences the observed duration behaviour. Only with a possible future availability of tick-by-tick bid-offer and/or volumn data from NYMEX would this study be possible.

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