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Two Essays on Intraday Information Processing of Stock Index Derivatives.

Raymond Waiman So
Louisiana State University and Agricultural & Mechanical College

TWO ESSAYS ON INTRADAY INFORMATION PROCESSING OF STOCK INDEX DERIVATIVES

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Raymond Waiman So
B.B.A., The Chinese University of Hong Kong, 1988
M.B.A., The Chinese University of Hong Kong, 1991
August 1997

UMI Number: 9808783

UMI
300 North Zeeb Road
Ann Arbor, MI 48103

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Abstract

The purpose of this dissertation is to examine two issues in intraday information processing among the spot index and index futures and index options. The first issue is price discovery. The second one is volatility spillover, especially the asymmetric effects of innovations in one market on the volatility of other markets.

In this dissertation, data on the German stock and index derivative markets are employed. The choice of Germany is primarily due to data availability. Therefore, the German data employed here are mainly for illustrative purposes and this study is not country specific. The choice of German data is also justified on the grounds of the size of the German market and the increasing importance of Germany in worldwide economy.

The dissertation has five chapters. Chapter 1 is the introduction that covers the motivation and main findings of the dissertation. In addition, institutional details of the German security markets are also covered.

Chapter 2 presents the descriptive statistics of the derivative markets and those of the stock index. An understanding of these descriptive statistics is useful in choosing the appropriate econometric techniques in the analysis.

Chapter 3 examines the price discovery process. Apart from using Granger-causality tests to examine the lead-lag relationship between the index derivatives, this chapter contributes to the literature by examining the degree of information sharing in the stock index and index derivative markets. It is found that the spot index and index futures contain the most information in the price discovery process and there is there is contemporaneous causality relationship among the three securities.

Chapter 4 explores volatility spillovers between the index securities. This chapter extends Chapter 3 by examining the information processing mechanism through the second moment. It is found that volatilities of the three securities spillover to one another. Together with the evidence presented in Chapter 3, the three securities should be considered as a whole system in the intraday information processing mechanism.

Chapter 5 gives the summary and conclusions.

Chapter 1

Introduction

1.1 Introduction

1.1.1 Purposes and Objectives

The purpose of this dissertation is to study the intraday information processing mechanism in the stock index and index derivative markets (hereafter index securities). Recent, Fleming, Ostdiek and Whaley (1996) (FOW) (to be discussed in greater details in Chapter 3) studies price discovery among the three index securities (stock index, index futures and index options) in the U.S. They find that index futures lead index options and index options lead the spot index in price discovery. Motivated by FOW, this dissertation extends FOW by addressing intraday information sharing and volatility spillovers among the index securities.

In this dissertation, data on the German stock and index derivative markets are used. This is because of data availability and the special features of the data offer a better arena than the U.S. data for analysis. The focus here is on the hypotheses put forward and the data are only for illustrative purposes. Therefore, this dissertation is not primarily aimed to be a country specific study.[1]

The use of German data has additional advantages over the United States (U.S.) data. First, the German stock index, the Deutscher Aktienindex (DAX), is a "total

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[1] According to Wallace and Gernon (1991), data on one country can be used to highlight uniqueness of a specific country ("nation as an object") or to test the generality of findings ("nation as context"). Thus, the German data can be used to test the generality of empirical findings and the use of data on one nation does not necessarily mean a country specific study.

performance index." Different from other popular stock indices like the Standard and Poor 500 (S&P 500), the DAX reflects stock distributions in its calculation. This special feature of the DAX allows for the adjustments for price changes caused by subscription rights, stock splits, and dividends. This point is particularly important since there is no need to estimate dividend yields in the calculation of the implied DAX from prices of DAX options.[2]

Second, DAX futures and DAX options are traded electronically. Thus, the reported time is also the actual transaction time. One shortcoming in using U.S. data is that there could be delays in reporting trades. Consequently, the reported time may not be the actual transaction time. Such delays in reporting will induce additional biases in the study of intraday information processing. However, such biases do not exist in the German derivative markets.[3]

Third, DAX options are European style options, which make the valuation much easier. Unlike the American style options, DAX options do not have the feature of early exercise. Together with the "total performance" feature of the DAX, DAX options greatly simplify the valuation mechanism.

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2 This point is discussed in greater detail in Chapter 3.

3 Though there are no delays in reporting in the German derivative markets, delays in reporting can occur in the equity market.

Fourth, the literature on the information processing mechanism in the derivatives markets mainly covers the U.S. markets.[4] It is true that the U.S. derivatives markets are among the largest in the world and they have high trading activities. However, the use of a different dataset will provide additional insights to the pricing relationships between the spot and the derivative markets. It also serves the purpose of testing whether the extant empirical evidence documented in the literature is only specific to the U.S. markets.

Fifth, the literature on pricing relationships between the stock index and derivatives focuses on the U.S. markets only. The analysis is usually limited to the stock index and one derivative only.[5] The more sophisticated index derivatives like index options and options on index futures (index futures options) are often left out. This dissertation attempts to fill this gap by providing new empirical evidence from the German dataset, which also contains index options.

Sixth, there is a concern over the problem of data snooping. As put forward in Lo and MacKinlay (1990), empirical procedures without a theoretical background will introduce biases in results. Such biased empirical results are, in fact, special forms of data snooping. Since previous studies mainly employ U.S. data in the analyses, there

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4 There are studies addressing information processing in non-U.S. derivative markets. For example, Martikainen and Puttonen (1994) and Puttonen (1993) study the Finnish derivative markets; Grunbichler, Longstaff and Schwartz (1994) and Broussard, Booth and Loistl (1997) study the German derivatives markets and Abhyankar (1995) studies the U.K. derivative markets. Nevertheless, majority of empirical evidence are for the U.S. derivative markets.

5 Literature in this part is discussed in greater details in Chapter 3.

are potential biases, hence data snooping, in the empirical results. This study reduces the problem of data snooping by considering non-U.S. (German) data and by examining three index securities together.

Apart from these advantages, the use of German data is also justified since the German stock market is one of the world's largest developed equity markets. Market capitalization of the German stock market at the end of 1994 is US$470,519 millions (International Finance Corporation, 1995). It only ranked behind the U.S., Japan, and the United Kingdom (U.K.) in terms of market capitalization among the developed markets.[6] This point is very important because the German market does not suffer from severe problems of infrequent trading and poor liquidity. It is well documented in the literature that nonsynchronous trading will lead to biases in the empirical results.[7] Being a developed market, there are few known market imperfections in Germany. This point

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6 Despite its size, the German market is a relatively "thin" market when compared with other developed markets since trading is highly concentrated. For example, there are 7,770 listed domestic companies at the end of 1994 in the U.S., 2,070 in the U.K. and 2,205 in Japan; but there are only 417 listed domestic companies in Germany (International Finance Corporation, 1995). Moreover, trading is concentrated in large companies. The 30 constituent stocks of the DAX, alone represent 85% of total trade volume (Bühler and Kempf, 1995). Nevertheless, in terms of trading volume relative to the market capitalization, the German market ranked sixth in the world with a turnover ratio of 97.8%. It only ranked behind France among the developed markets (International Finance Corporation, 1995).

7 For example, one problem of nonsynchronous trading is the wide bid-ask spread. Return computed from transaction prices may reflect the bouncing between the bid and ask prices rather than any new information. Another problem is measurement errors, due to infrequent trading, on computing returns. The impact of measurement errors on computing returns can be found in Conrad and Kaul (1993).

is important since market imperfections will also affect the conclusions as noted in Evnine and Rudd (1985).[8]

The dataset in this study contains minute-by-minute data of the DAX and tick-by-tick transaction data of the DAX futures and the DAX options. Previous literature in the study of the information processing mechanism of index derivatives, e.g., Bhattacharya (1987) and Chan (1992), typically look at the information processing mechanism between the spot index and one derivative only.[9] A drawback of these studies is that the information processing roles of other stock derivatives are left out. In other words, there is an implicit assumption that 100% information processing occurs in the spot index and one index derivative only. One objective of this dissertation is to provide new evidence on the role of other derivatives in the intraday information processing mechanism. This is an integral part in the study of pricing relationships among the index derivatives. Furthermore, the pricing relationship becomes much more complicated when the whole system is considered together.

Given the features of the data, this dissertation will investigate two issues relating to intraday information processing among the index securities. More details are covered in the next section.

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8 For example, the apparent arbitrage profits in violations of put-call parity are illusory due to high transaction costs, a type of market imperfections.

9 A recent article by Fleming, Ostdiek and Whaley (1996) is the first one to address the issue of information processing among stock index, index futures and index options.

1.1.2 Organization

This dissertation consists of two essays (Chapters 3 and 4). Chapter 2 covers the descriptive statistics of the intraday behaviors of the German index securities. Chapter 1 serves as a background for this study.

The first essay, Chapter 3, studies the intraday pricing relationships among the stock index, index futures, and index options. Empirical works in the literature typically agree that index futures tend to lead spot indices, as found in Stoll and Whaley (1990).

The extant literature, however, focuses mainly on the lead-lag relationships between spot and futures prices. Econometric techniques like Granger Causality and Error Correction Models (ECM) are used extensively. Instead of a mere repeat of previous work using a new dataset, this study looks at the degree of information sharing between the spot market and index derivatives. This issue has important implications to investors. Instead of answering the question of whether index derivatives process information better (more efficiently) than the spot market, this study addresses the question of how efficient the index derivatives are in information processing relative to the spot market.

The second essay, Chapter 4, explores the lead-lag relationships between spot and derivative volatilities, the existence of common volatilities and the volatility spillover processes in the index derivative markets. Previous work here focuses on volatility spillovers among different national stock markets or among different national markets for the same security. For example, Bae and Karolyi (1994) look at the volatility spillovers between New York and Tokyo stock markets; Koutmos and Booth (1995) examine

volatility spillovers among the New York, London and Tokyo equity markets; Tse, Lee and Booth (1996) investigate the volatility spillovers of Eurodollar futures among markets in Singapore (SIMEX), London (LIFFE) and Chicago (IMM). However, little is done to examine the volatility spillover process among similar securities in the same national market.[10]

This essay contributes to the literature by looking at the lead-lag relationships and volatility spillovers among volatilities of the index derivatives. Most important, the essay explores the asymmetric spillover effects by examining the differences between good and bad news. Since the first essay looks at the information processing mechanism through the first moment (price discovery), this chapter extends the first essay by examining the information processing mechanism through the second moment (volatility spillovers).

1.1.3 Lindley's Paradox and Significance of Statistical Testing

According to Lindley (1957), lower significance levels may be required for larger samples. Otherwise, there will be spurious significance results because of large sample size distortions. This is known as the Lindley's Paradox in the literature. This point is particular important in studies using transaction data. Recognizing the Lindley's Paradox, Chan (1992), Tse and Booth (1996) and Broussard, Booth and Loistl (1997) apply lower significance levels in their studies. Since the amount of data in this dissertation is huge, lower significance level is needed. Following Chan (1992), the significance level in this study is set to be 0.1% if there are 10,000 or more observations

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[10] Koutmos and Tucker (1996) is one of the few studies that address volatility spillovers across derivatives in the same domestic market. Detailed literature review is in Chapter 4.

in the sample. For sample size larger than 5,000 but smaller than 10,000, the significance level is set to be 0.5%. One percent significance level is used for sample size of one to 5,000 observations.

1.2 Stock Index Derivatives

A derivative is a financial instrument whose payoffs depend on ("derived from," hence the name derivative) an underlying asset. Thus, the prices of derivatives are related to the prices of the underlying assets. Typical examples of derivatives include futures, options and swaps, to name but a few. The advantages of derivatives include market completeness, better risk hedging, leverage and more efficient information processing. Detailed discussion of derivatives can be found in standard textbooks in derivatives like Daigler (1994), Hull (1993) and Kolb (1994).

1.2.1 Stock Index Futures

A futures contract is a standardized contract in which the buyer and the seller agree to trade the underlying asset at a specified quantity for a specified price on a specified date. In case of stock index futures, the underlying asset is the stock index itself. The buyer and seller then agree to settle in cash the difference in the stated price and the settlement price. If the settlement price is higher (lower) than the purchase price, then the buyer (seller) gains.

1.2.2 Stock Index Options

Stock index options give the buyer the right, but not the obligation, to buy or sell the stock index at a specified price on or before a specified day (American options) or at a specified date (European options). There are two types of options: put options and

call options. A call option will give the holder the right to buy, while a put option gives the holder the right to sell. The pre-determined price is called the exercise price.

1.3 Data Sources

Detailed description of the data and how the data series are constructed will be given in the respective chapters. This section just provides a brief overview of the data sources.

Minute-by-minute data on the DAX are from the Frankfurt Stock Exchange (FSE). Tick-by-tick transaction data on index futures (FDAX) and index options (ODAX) are obtained from the German Futures and Options Exchange, the Deutsche Terminbörse (DTB). Data on the DAX, the FDAX and the ODAX cover the time period January 1, 1992 to March 31, 1994. Table 1.1 shows the sample content of the data used.

Panel A of Table 1.1 gives the sample content of the DAX data. The DAX is reported once a minute and at the same second throughout the day (to be discussed in the next section). Panels B and C show the sample data for the FDAX and the ODAX. The transactions of both securities are "time stamped" to the nearest 1/100 of a second.

1.4 Institutional Details of Trading in Germany

1.4.1 DAX Construction and Stock Trading

Trading of common stocks in Germany can be done primarily either through floor trading or through electronic trading. For the floor trading, there are eight different stock exchanges in eight major cities: Berlin, Bremen, Dusseldorf, Frankfurt, Hamburg, Hanover, Munich and Stuttgart. The FSE, however, is the dominant stock exchange.

Table 1.1

Sample Contents of the DAX, FDAX and ODAX Datasets

Panel A: Sample Data of the DAX

Date	Time	DAX Level
920102	10:33:24	1602.30
920102	10:34:24	1604.73
920102	10:35:24	1605.21
920102	10:36:24	1607.01
920102	10:37:24	1608.10

Panel B: Sample Data of the FDAX

Product	Ex Month	Ex Year	Year	Mt	Dy	Hr	Mn	Sc	Cs	Price	Volume
FDAX	03	92	1992	01	02	09	35	29	00	1626.00	108
FDAX	03	92	1992	01	02	09	35	33	02	1627.50	1
FDAX	03	92	1992	01	02	09	35	37	57	1628.00	5
FDAX	03	92	1992	01	02	09	35	47	32	1628.00	2
FDAX	03	92	1992	01	02	09	35	58	63	1628.00	7

(table cont'd.)

Panel C: Sample Data of ODAX														
Product	Ty	Ex Mt	Ex Yr	Ex Price	Yr	M t	D y	Hr	M n	Sc	Cs	Price	Volume
ODAX	C	01	92	1500	1992	01	02	12	25	17	27	115	10
ODAX	C	01	92	1500	1992	01	03	12	07	30	97	115	15
ODAX	C	01	92	1500	1992	01	07	12	36	02	00	101.50	15
ODAX	C	01	92	1500	1992	01	07	13	30	09	48	97	10
ODAX	C	01	92	1500	1992	01	08	14	08	49	54	82	20

In Panel A, the reported second is the same throughout a given day. In Panel B, Ex month represents the expiratory month of the futures contracts, Ex Year represents the expiratory year. Year, Mt, Dy, Hr, Mn Sc and Cs give, respectively, the calendar year, month, day, hour, minute, second and 1/100th second at which the trade occurs. In Panel C, Ty represents the type of options, with a "C" for call and a "P" for put. Ex Mt, Ex Yr, Ex Price are the expiratory month, expiratory year and exercise prices of the options. Yr, Mt, Dy, Hr, Mn, Sc, Cs are, respectively, the calender year, month, day, hour, minute, second and 1/100th at which the trade occurs. Price and Volume in both Panels B and C denote the price and volume of the transaction.

The FSE opens from 10:30 a.m. to 1:30 p.m. German time. For the electronic trading, investors can execute their orders through the Integriertes Börsenhandels - und Informations - System (IBIS). The trading hours of IBIS are from 8:30 a.m. to 5:00 p.m. German time. Recently, Grunbichler, Longstaff and Schwartz (1994) (GLS) conclude that FDAX trading via the electronic trading system is more efficient in information processing than common stock trading through floor trading. However, as pointed out by Broussard et al. (1997), the conclusion in GLS is highly suspect since GLS completely ignore the existence of a parallel electronic stock trading system, the IBIS.

The DAX is calculated once a minute and at the same second for every minute to reflect the values of the component stocks. The second is determined daily by the time of the first trade within the minute. For example, if the first trade on a given day occurs at 10:33:24, then the DAX will be reported at the 24th second of the minute throughout the same day.

The DAX is a capital-weighted index of the stock prices of 30 of Germany's largest companies. The DAX is calculated and reported up to two decimal places. As noted in the introduction, the DAX reflects stock distributions in its calculation (e.g., subscription rights, stock splits, and dividends). In this way, the DAX is a "total performance index," at least on a pre-tax basis. Adjusting for dividends is done by reinvesting the dividends paid into the dividend paying stock. A complete list of these 30 companies is given in Panel A of Table 1.2. In this list, there are familiar names like Daimler Benz, BASF, Lufthansa, Volkswagon, etc. Panels B and C of the same table

Table 1.2

Constituent Stocks in the DAX and Summary Statistics of Prices and Daily Trading Volume

Panel A: Constituent Stocks in the DAX

1. Allianz	11. Deutsche Bank	21. Metallgesellschaft
2. BASF	12. Degussa	22. Mannesmann
3. Bayer	13. Dresdner Bank	23. Preussag
4. Bayrische Hypobank	14. Henkel	24. RWE
5. BMW	15. Hoechst	25. Schering
6. Bayrische Vereinsbank	16. Karstadt	26. Siemens
7. Commerzbank	17. Kaufhof Holding	27. Thyssen
8. Continental	18. Lufthansa	28. VEBA
9. Daimler-Benz	19. Linde	29. VIAG
10. Deutsche Babcock	20. MAN	30. Volkswagon

Panel B: Summary Statistics of Prices of DAX Constituent Stocks

Stock	Summary Statistics			
	Mean	Median	Maximum	Minimum
Allianz	2294.14	2272.51	3068.55	1640.33
BASF	247.51	244.84	327.93	200.94
Bayrische Vereinsbank	452.31	426.65	593.31	379.97
Bayer	296.62	292.33	387.93	239.90
Bayrische Hypobank	423.60	409.77	529.13	359.32
BMW	575.74	556.41	881.63	447.63
Commerzbank	289.96	268.63	398.91	215.60
Continental	236.93	237.08	296.92	185.25
Daimler-Benz	699.54	738.94	872.77	505.50
Degussa	367.55	345.62	529.70	276.07
Deutsche Bank	727.14	711.42	895.73	595.88
Deutshce Babcock	181.46	171.82	284.61	122.60
Dresdner Bank	379.74	365.38	467.66	311.68
Henkel	589.34	592.40	662.57	520.02
Hoechst	263.35	257.80	337.85	215.61
Karstadt	572.30	570.80	661.98	471.95
Kaufhof Holding	485.88	491.88	585.94	383.93
Linde	797.58	809.34	947.95	656.29
Lufthansa	139.04	145.65	208.03	85.12
MAN	336.53	331.73	455.67	240.15
Mannesmann	298.94	285.44	436.05	201.34
Metallgesellschaft	347.36	348.65	455.75	179.67
Preussag	391.96	394.87	492.49	302.80

(table cont'd.)

RWE	418.52	403.15	525.64	364.66
Schering	854.90	808.49	1156.01	637.59
Siemens	658.18	665.25	796.08	536.87
Thyssen	212.60	215.69	280.02	149.30
VEBA	405.43	388.15	527.23	338.45
VIAG	398.41	384.69	507.37	295.22
Volkswagon	357.64	362.29	508.00	235.49
Overall	490.03	397.93	3068.55	85.12
30 Dow Jones Companies (in US$)	54.34	57.35	102.67	15.42

Panel C: Summary Statistics of Trading Volume of DAX Constituent Stocks

Stock	Summary Statistics			
	Mean	Median	Maximum	Minimum
Allianz	9076.06	8157.5	28432	850
BASF	61181.30	55752.5	173301	8450
Bayrische Vereinsbank	24705.86	21261.0	122066	4750
Bayer	48000.95	42485.0	268746	6700
Bayersche Hypobank	26515.58	23186.5	75374	5550
BMW	19359.48	15961.0	79953	2416
Commerzbank	56199.96	48608.5	277198	10101
Continental	17826.58	15333.5	65750	1050
Daimler-Benz	33685.05	26049.0	134148	2450
Degussa	15721.39	14049.5	70441	2518
Deutsche Bank	37924.97	33287.5	162778	6317
Deutshce Babcock	15897.64	14408.5	70452	2003
Dresdner Bank	38199.76	33093.5	401354	5591
Henkel	11073.59	9987.5	34790	1785
Hoechst	49112.34	43863.0	198257	9700
Karstadt	12550.41	11328.5	69499	2542
Kaufhof Holding	6144.11	5090.5	39180	494
Linde	8264.47	7361.0	35330	1147
Lufthansa	34454.07	29947.0	124112	3750
MAN	17273.62	15760.0	63666	1800
Mannesmann	44851.70	39752.0	164243	2350
Metallgesellschaft	21773.26	14155.0	186871	1200
Preussag	22900.90	19696.5	191572	2700
RWE	28013.92	24985.5	128360	1950
Schering	11746.94	9795.5	47541	100
Siemens	29827.09	27778.5	151038	5314
Thyssen	38484.11	36549.5	109621	2700
VEBA	35194.25	34356.5	304588	2683
VIAG	21462.07	17137.0	171422	738
Volkswagon	26442.53	22802.0	75528	4050
Overall	27464.97	28020.0	401354	100
30 Dow Jones Companies	996994.8	810913.9	2446507	330688.1

show the descriptive statistics of the price and trading volume of these 30 companies throughout the sample period. Two interesting points can be observed from this panel. First, these German stocks have very high prices.[11] The average price of the 30 DAX stocks is DM490.03 (US$ 302.47), which is much higher than the average price (US$ 54.34) of the 30 Dow Jones companies in the U.S. for the same period.[12] Second, the daily trading volumes of the German stocks are rather "thin." On average, the daily trading volume of the 30 DAX stocks is 27,464.97 shares while that of the 30 Dow Jones companies is 996,994.8 shares. This observation of "thin trading" is consistent with the findings in Bühler and Kempf (1995).

1.4.2 FDAX and ODAX Trading

The FDAX and ODAX contracts are traded through the electronic system at the DTB. Trading hours are from 9:30 a.m. to 4:00 p.m. German time. For the ODAX, it is a European-style option. Detailed contract specifications of the FDAX and the ODAX are contained in Table 1.3 and Table 1.4.

1.5 Summary

In this dissertation the intraday information processing mechanism among the index securities is examined. By examining the price discovery and volatility spillovers

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[11] Recently, the prices of the German stocks begin to be more in par with those in other countries. For example, the price of one share of BASF at the end of November 1996 is around DM52, which is much lower than the average price of DM247.51 for the sample period.

[12] The US$ equivalent is calculated by using average daily US$/DM exchange rate (one US$=1.6201196DM) for the sample period January 1992 to March 1994.

Table 1.3

Specifications of the FDAX Contracts

Contract Size:	100 Deutschemark (DM) per DAX index point.
Quotation:	In points, with one decimal place.
Minimum Price Movements:	0.5 point.
Settlement Months:	The three nearest months of the cycle March, June, September, December
Last Trading Day:	The exchange trading day prior to the respective final settlement day.
Final Settlement Day:	The third Friday of the respective settlement month if that is an exchange trading day, otherwise the exchange trading day immediately preceding this Friday.
Settlement:	Cash settlement based on the final settlement price, due the second exchange trading day following the last trading day.
Final Settlement Price:	The value of the DAX index calculated on the basis of the opening prices fixed by the Frankfurt Stock Exchange for the DAX-listed shares on the final settlement day.
Trading Hours:	9:30 a.m. - 4:00 p.m. German time.

Table 1.4

Specifications of the ODAX Contracts

Contract Size:	DM 10 per DAX index point.
Quotation:	In points, with one decimal place.
Minimum Price Movements:	0.1 point.
Expiration Months:	Options are available for the nearest months as well as the next two quarterly expiration months (March, June, September, December).
Expiration Day:	The expiration day of an option series is the exchange trading day following its last trading day.
Last Trading Day:	The third Friday of the expiration month if that is an exchange trading day, otherwise the exchange trading day immediately preceding this Friday. Trading in the expiring series closes at 1:30 p.m. Frankfurt time on the last trading day.
Exercise:	European-style.
Settlement:	Cash settlement on the first exchange trading day after the last trading day.
Final Settlement Price:	The average value of the DAX calculations performed at the Frankfurt Stock Exchange from 1:21 p.m. to 1:30 p.m. Frankfurt time on the last trading day of the option series.
Exercise Prices:	Exercise price intervals are in increments of 25 index points (e.g., 2125, 2150, 2175). Five exercise prices are introduced for each contract month.
Option premium:	The DM-equivalent of the premium in points is payable in full on the exchange trading day following the day the option was purchased.
Trading Hours:	9:30 a.m. - 4:00 p.m. German time.

among the index securities, this dissertation contributes to the literature by providing new evidence on the intraday information processing mechanism among index securities.

Results from price discovery show that spot index and index futures have larger information sharing than index options. In terms of lead-lag relationships, returns of the three index securities exhibit contemporaneous interaction effects. Returns of one security will have forecasting power over returns of the other securities. Consequently, the three index securities all contribute to the intraday price discovery process and they should be considered as a whole system in the information processing mechanism.

Results from the chapter on volatility spillovers shows that there does not exist a common volatility process among the DAX securities in short term intraday volatilities. However, a common volatility exists over a longer time span. Volatilities of the three DAX securities are found to spillover to one another. Overall results support the notion that the three DAX securities all perform intraday information processing.

In summary, markets for the three DAX securities exhibit interaction effects in their intraday pricing and volatility relationships. Consequently, all the three securities contribute to the discovery and transmission of new information.

Chapter 2

Descriptive Statistics of Intraday Behavior of Index Securities: Evidence From The German Markets

2.1 Introduction

This chapter provides some descriptive statistics of the intraday behaviors of the returns of the DAX, the FDAX and the ODAX (hereafter the DAX securities). An understanding of these descriptive statistics is useful. First, previous studies, e.g., McInish, Wood and Ord (1985), Peterson (1990) and Hilliard and Tucker (1992), document different intraday patterns in volatilities in equities, equity options and commodity futures markets. These works, however, focus on the United States (U.S.) markets only. The study of intraday behaviors of the DAX securities enables the examination of whether these intraday trading patterns are specific to the U.S. markets only. Second, econometric analyses require certain assumptions of the data generating processes. For example, the Exponential Generalized Autoregressive Heteroscedasticity (EGARCH) model used in the study of asymmetric volatility spillovers (see Chapter 4) requires the variance of security returns to be heteroscedastic. If the variances of returns of the DAX securities are instead homoscedastic, modeling the variances with EGARCH models is inappropriate. Therefore, an understanding of the data generating processes will be useful in choosing the appropriate econometric techniques in data analysis.

2.2 Datasets Construction

Intraday behaviors of returns of the DAX securities are studied here. In constructing the intraday return series, return of a fixed time interval is used. In deciding a suitable interval, the tradeoff between noise and information has to be

considered. The intervals should not be too large; otherwise, they will not capture the information contained in the intraday return patterns. However, if the intervals are too narrow, much noise will be embedded in the dataset instead. Since the DAX is updated every minute, theoretically, minute-by-minute return of the DAX can be used. As noted before, the noise introduced by minute-by-minute returns will also be high. Besides, there is no guarantee that the FDAX and the ODAX are traded in every minute. Maintaining a balance between these two considerations (information against noise), this dissertation uses five, 15 and 30 minutes intervals. They are chosen for two principal reasons. First, the DAX is only reported during the three hours of trading at the Frankfurt Stock Exchange (FSE). If hourly return is used, then at most three observations are available each day. In this way, much intraday information is lost. Second, these three different time intervals can be used as checks to the robustness of empirical results.

To construct the intraday returns of the DAX securities, the last observed prices of the DAX securities in a given interval are used.[1] For example, if there are six trades of the FDAX in the same five minute interval, price of the last trade will be used. In this way, it is assumed the last price will contain most recent information. If no trade occurs within this five-minute interval, price of the previous five minute interval is used. In doing this, an implicit assumption is that there is no new information and the prices do not change. Return is then defined as:

$$\mathrm{Ret}_{j,t} = \ln(P_{j,t} / P_{j,t-1}), \tag{2.1}$$

[1] Data on quotes of the DAX securities are not available.

where $Ret_{j,t}$ is the log return (first difference of natural logarithms) of security j (j=DAX, FDAX and ODAX) at time t; $P_{j,t}$ is the price of security j at time t and $P_{j,t-1}$ is the price of security j at time t-1.

The use of DAX data is straightforward since the DAX is reported every minute once the first reporting occurs. For the FDAX contracts, only the nearby contracts are considered. It is because the trading volume of nearby FDAX contracts always dominates those of other maturities. Panel A of Table 2.1 depicts the average number of trades of nearby and non-nearby FDAX contracts per minute. The trading activities of nearby contracts are much heavier than those of non-nearby contracts. During the trading hours of the German Futures and Options Exchange (DTB), there are on average 5.61 FDAX contracts traded per minute, in which 5.20 (92.7%) are nearby contracts. Note that the DTB opens before and closes after the FSE. Before the FSE opens, 92.5% of trades are nearby contracts; when the DTB and the FSE are open concurrently, the percentage is 93.3%; and the percentage becomes 92.1% after the FSE closes. The observation of heavy trading concentrates in nearby contracts thus does not change across time of the day.

To illustrate this point further, Figure 2.1 shows the daily number of trades for all the 1992 FDAX contracts throughout their maturities. As evidenced in Figure 2.1, the trading activities of FDAX are always concentrated in the nearby contracts.[2] One important observation can be made from Figure 2.1. The trading activity of the next nearest contract becomes more intense once the preceding contract enters its expiring

[2] Trading patterns of other FDAX contracts are similar and not reported here.

Table 2.1

Average Number of Trades of FDAX and ODAX Per Minute by Contract Types and Time of The Day

Panel A: FDAX Contracts

Time of the Day	All	Nearby	Non-Nearby
DTB Trading Hours	5.61	5.20	0.40
Before FSE opens	6.81	6.30	0.51
Trading concurrently with FSE	6.07	5.66	0.41
After FSE closes	4.57	4.21	0.36

Panel B: ODAX Contracts

Time of the Day	All	Nearby	Non-Nearby
DTB Trading Hours	4.03	2.01	2.02
	(2.05)	(1.06)	(0.99)
	[1.98]	[0.96]	[1.03]
Before FSE opens	4.32	2.37	1.94
	(2.23)	(1.26)	(0.97)
	[2.09]	[1.11]	[0.97]
Trading concurrently with FSE	4.35	2.13	2.21
	(2.21)	(1.12)	(1.09)
	[2.13]	[1.00]	[1.13]
After FSE closes	3.54	1.73	1.81
	(1.77)	(0.90)	(0.88)
	[1.77]	[0.83]	[0.93]

"DTB trading hours" refers to the average number of trades per minute throughout the trading hours of the DTB. All refers to all contracts included; while Nearby (Non-Nearby) refers to nearby (non-nearby) contracts only. For the ODAX, numbers in parentheses refer to the average number of call options traded; and numbers in brackets refer to the average number of put options traded.

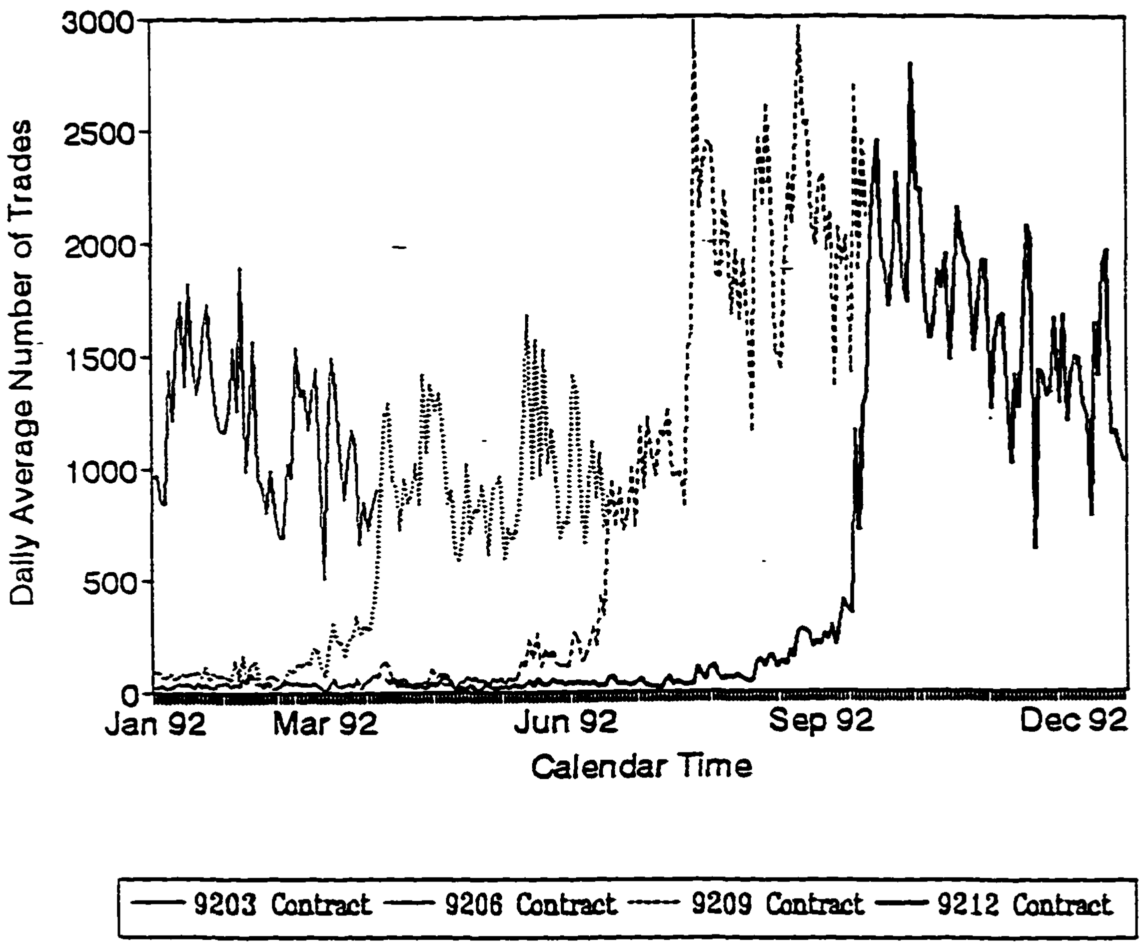

Figure 2.1

Daily Average of Trades of FDAX Contracts: For All 1992 Contracts

month. Nevertheless, nearby contracts are still the most heavily traded ones. The intraday returns of the FDAX are then calculated from the prices of the nearby FDAX contracts since heavy trading will reveal information more efficiently.

Another interesting observation is that trading volumes of the FDAX and ODAX contracts decrease when the FSE is closed. For example, on average, there are 6.81 FDAX contracts traded per minute before the FSE opens. However, there are only 4.57 contracts traded after the FSE closes. According to Copeland (1976), trading volume can be proxied for the flow of information. The heavy trading before FSE opens can be attributed to the accumulation of overnight information and investors tend to act once the market opens. When the FSE opens, FSE and DTB together perform the roles of price discovery and thus heavy trading. After the FSE closes, investors can only trade stocks through the IBIS system; and the number of trades in stocks is lowered. From the information-volume perspective, there is a lower information flow from the spot market and the trading volume of FDAX contracts decreases.

For the ODAX, the calculation of intraday returns is not as straightforward as those in the DAX and the FDAX. First, there is the selection problem. For example, there are more than 100 option contracts (different maturities, different exercise prices, puts and calls) traded in January 1992. Choosing a particular ODAX contract in the calculation of intraday returns is not easy. Second, there is the nonsynchronous problem, even using "real time" data from the DTB. Although the total trading volume of option contracts is huge, the trading volume of individual ODAX contract is much smaller than that of the FDAX. The problem of thin trading also creates some "quasi-anomalies."

For example, Evnine and Rudd (1985) document significant violations of arbitrage conditions and put-call parity in intraday Major Market Index (MMI) and S&P 100 index options prices. They conjecture that such violations are due to market imperfections and nonsynchronous prices in hectic trading conditions.

To resolve the problem of nonsynchronous trading, this dissertation follows the approach in Fleming, Ostdiek and Whaley (1996) (FOW). FOW employ Roll's (1977) American option pricing model to imply the cash index. In this way, they do not have to pick a particular option contract in computing option return since all option contracts can be used to imply the "cash index." Thus, the selection problem is circumvented. In addition, as the choice of option contracts increase, the problem of nonsynchronous trading of individual option contract becomes less severe. Since the ODAX is a European type option, this dissertation uses the Black-Scholes (1973) (B-S) European option pricing models to imply the DAX value.[3]

Panel B of Table 2.1 shows that the average number of ODAX contracts traded per minute by time of the day. Contrary to the case of the FDAX, the nearby and non-nearby ODAX contracts have similar trading volumes. The percentage of trading volume of non-nearby contracts traded to total trading volume is almost 50%. This observation is contrary to the findings of the FDAX. However, the definition of non-nearby contracts for the ODAX is very much different from that of the FDAX. At the beginning of each month, the DTB will introduce nearby ODAX with maturity of one month or less. In this way, "nearby" ODAX contracts are those close to their

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[3] Calculation of the implied DAX is given in details in Chapter 3.

expirations. Many actively traded ODAX contracts are classified as "non-nearby" contracts because they have maturities greater than one month. Thus, a more broad definition of "nearby" contracts for the ODAX is necessary.

Table 2.2 shows the proportion of trading volume of different ODAX contracts according to their moneyness and their time to maturity. Moneyness is defined as 100 * (S/X - 1) for call options and 100 * (1 - S/X) for put options, where S is the current stock index, and X is the exercise price. Maturity is defined as the number of months to expiration. As evidenced from Panel A of Table 2.2, the most heavily traded option contracts are at-the-money options with a maturity of one to two months. An interesting point can be observed here. The farther away from moneyness and maturity, the ODAX contract will be less actively traded. Panels B and C report the trading volumes for call and put options respectively. Similar results are obtained for the call and put options. From the perspective of information processing, more actively traded instruments can reveal information more efficiently (Copeland (1976)). Therefore, this dissertation uses those at-the-money options with maturities less than two months to imply the DAX.[4]

Prices of the DAX securities are defined to be the actual DAX and FDAX values for the DAX and FDAX series, and the implied DAX for the ODAX series. To find the implied DAX from ODAX prices, the inputs of the B-S models are needed. To capture

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[4] Following FOW, those options with maturities less than nine days are excluded. This is because there is a drastic increase in the implied volatilities of options when they approach expiration. Since options with maturities of two months or less are the most actively traded, this dissertation only uses at-the-money options with a maturity of less than 60 but more than nine days. At-the-money options are defined as those options with moneyness within $\pm$ 2.5%.

Table 2.2

Proportion of Trading Volume of ODAX by Option Moneyness and Months to Expiration For the Period January 1992 to March 1994

Panel A: Proportion of Trading Volume: All Contracts

	Months To Expiration (T)				
Moneyness (M)	< 1	$1 \le T < 2$	$2 \le T < 3$	$3 \le T < 4$	$4 \le T < 5$
$M < -10.00$	0.00	0.02	0.01	0.00	0.00
$-10.00 \le M < -7.5$	0.01	0.03	0.02	0.01	0.01
$-7.5 \le M < -2.5$	0.03	0.08	0.03	0.01	0.01
$-2.5 \le M < -0.0$	0.12	0.14	0.04	0.01	0.01
$0.0 \le M < 2.5$	0.10	0.08	0.02	0.01	0.00
$2.5 \le M < 5.0$	0.03	0.02	0.01	0.00	0.00
$5.0 \le M < 10.0$	0.01	0.01	0.01	0.00	0.00
$M > 10.0$	0.01	0.00	0.00	0.00	0.00

Panel B: Proportion of Trading Volume: Call Options Only

	Months To Expiration (T)				
Moneyness (M)	< 1	$1 \le T < 2$	$2 \le T < 3$	$3 \le T < 4$	$4 \le T < 5$
$M < -10.00$	0.00	0.01	0.00	0.00	0.00
$-10.00 \le M < -7.5$	0.00	0.01	0.01	0.01	0.00
$-7.5 \le M < -2.5$	0.02	0.04	0.02	0.01	0.00
$-2.5 \le M < -0.0$	0.07	0.08	0.02	0.01	0.00
$0.0 \le M < 2.5$	0.05	0.04	0.01	0.00	0.00
$2.5 \le M < 5.0$	0.02	0.01	0.00	0.00	0.00
$5.0 \le M < 10.0$	0.01	0.01	0.00	0.00	0.00
$M > 10.0$	0.01	0.00	0.00	0.00	0.00

(table cont'd.)

Panel C: Proportion of Trading Volume: Put Options Only					
	Months To Expiration (T)				
Moneyness (M)	< 1	1 ≤ T < 2	2 ≤ T < 3	3 ≤ T < 4	4 ≤ T < 5
M < -10.00	0.00	0.01	0.01	0.00	0.00
-10.00 ≤ M < -7.5	0.01	0.02	0.01	0.00	0.00
-7.5 ≤ M < -2.5	0.01	0.03	0.01	0.00	0.00
-2.5 ≤ M < -0.0	0.05	0.07	0.02	0.01	0.00
0.0 ≤ M < 2.5	0.05	0.05	0.01	0.01	0.00
2.5 ≤ M < 5.0	0.01	0.01	0.01	0.00	0.00
5.0 ≤ M < 10.0	0.01	0.01	0.01	0.00	0.00
M > 10.0	0.00	0.01	0.00	0.00	0.00

Moneyness for put options is defined as M=100*(1-S/X), where S is the current DAX level and X is the exercise price of the put; moneyness for call options is defined as M=100*(S/X-1), where S and X are as previously defined. Negative values of M are therefore out-of-the-money options and positive values are in-the-money options. Proportion of trading volume is defined as the proportion of trading volume of the options within the categories to all options traded within the period January 1992 to March 1994. A total of 44,338,363 option contracts are traded.

possible intraday changes in implied volatilities, three estimates of implied volatilities are used. Implied volatilities are calculated by using trades in previous fifteen minutes, previous hour and previous day. These estimates of implied volatilities can also be used to cross-check the robustness of empirical results. Since calls and puts may not have the same characteristics, the whole sample is further divided into puts and calls. Summary statistics of the intraday returns of DAX securities are presented in Table 2.3.

2.3 Summary Statistics

Table 2.3 presents the summary statistics of the intraday returns of the DAX securities. An examination of Table 2.3 shows that the distributions of the intraday returns of the DAX securities are not normal. No matter which data collection procedure is used, the Kolmogorov-Smirnov D statistics are still significant for all the three DAX securities at the 0.1% level. The general conclusion is that the intraday returns of the DAX securities are not normally distributed. This finding is consistent with earlier work on the distribution of futures price changes documented in Helms and Martell (1985).

Apart from testing the normality of the intraday returns of the DAX securities, several interesting points can be observed here. First, call ODAX exhibits higher excessive kurtosis than the put ODAX. However, variance and range of return of the put options are higher than those of the calls. These characteristics show that intraday behaviors of returns of calls and puts are different. At a first glance, this finding is surprising since put and call options should be the same because of the put-call parity. The different behaviors of put and call options mean that there is a violation of put-call parity, which implies market inefficiency. However, as put forward in Evnine and Rudd

Table 2.3

Summary Statistics of Intraday Returns of the DAX Securities For the Period January 1992 to March 1994

Panel A: Five Minute Return

	Summary Statistics						
Securities	Mean	Variance	Skewness	Kurtosis	D	Max	Min
DAX	-2.93E-6	6.17E-7	-1.117	34.270	0.800	0.008	-0.021
FDAX	-1.00E-5	8.21E-7	-0.245	3.976	0.153	0.006	-0.011
ODAX1	-2.00E-5	5.07E-6	0.176	13.932	0.102	0.036	-0.027
ODAX2	-2.00E-5	4.44E-6	0.122	15.589	0.105	0.036	-0.028
ODAX3	-2.00E-5	4.12E-6	0.235	15.999	0.105	0.036	-0.022
ODAX4	-3.44E-6	1.80E-5	0.035	2.090	0.095	0.022	-0.022
ODAX5	-4.29E-6	1.60E-5	0.048	2.072	0.099	0.022	-0.023
ODAX6	-4.63E-7	1.50E-5	0.019	2.424	0.101	0.025	-0.028

Panel B: Fifteen Minute Return

	Summary Statistics						
Securities	Mean	Variance	Skewness	Kurtosis	D	Max	Min
DAX	2.817E-6	1.871E-6	-0.116	1.873	0.034	0.009	-0.008
FDAX	-2.00E-5	2.172E-6	-0.395	5.838	0.101	0.010	-0.016
ODAX1	-5.00E-5	7.976E-6	0.091	3.592	0.056	0.019	-0.017
ODAX2	-5.00E-5	6.147E-6	0.019	4.050	0.061	0.016	-0.016
ODAX3	-5.00E-5	5.232E-6	0.038	3.620	0.051	0.017	-0.015
ODAX4	-4.00E-5	2.50E-5	-0.088	1.113	0.036	0.020	-0.027
ODAX5	-4.00E-5	1.90E-5	-0.029	1.148	0.046	0.020	-0.023
ODAX6	-3.00E-5	1.80E-5	-0.033	1.134	0.046	0.018	-0.021

(table cont'd.)

Panel C: Thirty Minute Return							
	Summary Statistics						
Securities	Mean	Variance	Skewness	Kurtosis	D	Max	Min
DAX	1.40E-5	3.67E-6	-0.255	2.194	0.032	0.012	-0.012
FDAX	-5.00E-5	3.88E-6	-0.399	4.690	0.089	0.011	-0.018
ODAX1	-1.70E-5	8.75E-6	0.065	2.618	0.052	0.017	-0.018
ODAX2	-0.0001	9.05E-6	0.217	3.182	0.050	0.018	-0.015
ODAX3	-8.00E-5	7.41E-6	0.110	3.578	0.049	0.018	-0.019
ODAX4	-4.34E-5	2.50E-5	-0.068	0.826	0.028	0.019	-0.023
ODAX5	-6.00E-5	2.40E-5	0.031	1.226	0.033	0.020	-0.024
ODAX6	-3.00E-5	2.10E-5	-0.052	1.173	0.039	0.018	-0.021

D is the Kolmogorov-Smirnov statistics for testing normality. The D statistics are significant at the 0.1% level. ODAX1 is the call ODAX estimated from implied volatility using trades in the past 15 minutes, ODAX2 is the call ODAX estimated from implied volatility using trades in the past hour, ODAX3 is the call ODAX estimated from implied volatility using trades in the past day, ODAX4 is the put ODAX estimated from implied volatility using trades in the past 15 minutes, ODAX5 is the put ODAX estimated from implied volatility using trades in the past hour, ODAX6 is the put ODAX estimated from implied volatility using trades in the past day.

(1985), market imperfections like transaction costs and infrequent trading will lead to violations of the put-call parity; and the arbitrage profits from put-call parity violations are just illusory. Because of puts and calls have different intraday return patterns, separating these two kinds of options in the analyses will be more appropriate.

Second, returns of the ODAX, both puts and calls, show the highest variance; and variance of the FDAX is also larger than that of the DAX. Besides, the range of returns of the ODAX is also largest among the three DAX securities. According to Ross (1989), variances can be proxied for information. The differences in variances then imply differences in information processing among the DAX securities.

These summary statistics show that the behaviors of the intraday returns of the three DAX securities are very different from one another. Consequently, they may share different roles in the intraday information processing mechanism.

2.4 Autocorrelation and ARCH Effects

This section discusses the patterns of autocorrelation and variance of the intraday returns of the DAX securities.

2.4.1 Autocorrelation

The autocorrelations of the intraday returns of the DAX securities are given in Table 2.4. The Ljung-Box statistics are significant for all the DAX securities.[5] The null hypothesis of all autocorrelations at lags one to six are equal to zero is rejected. Several

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[5] Alternatively, the Q-statistics in section 2.4.2, which are used to test the nonlinear effects, can be employed to examine the presence of autocorrelation. Since autocorrelation is a linear concept, the Ljung-Box statistics are used here for its simplicity in calculation.

Table 2.4

Autocorrelation of Minute-By-Minute Returns of DAX Securities

Panel A: Five Minute Return

Securities	Autocorrelation at Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Ljung-Box χ^2
DAX	0.181	-0.060	-0.003	0.022	0.029	0.015	688.15***
FDAX	-0.024	-0.059	-0.016	0.029	0.010	0.038	119.91***
ODAX1	-0.255	-0.058	-0.055	-0.025	0.012	0.003	1307.36***
ODAX2	-0.281	-0.030	-0.024	-0.006	0.004	-0.009	1464.12***
ODAX3	-0.294	-0.030	-0.028	0.002	0.005	-0.014	1605.28***
ODAX4	-0.350	-0.055	-0.066	-0.001	-0.006	0.007	2356.27***
ODAX5	-0.380	-0.045	-0.020	-0.001	-0.002	-0.004	2657.39***
ODAX6	-0.385	-0.040	-0.023	0.001	-0.000	-0.002	2732.00***

Panel B: Fifteen Minute Return

Securities	Autocorrelation at Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Ljung-Box χ^2
DAX	0.057	0.073	0.031	-0.011	0.003	-0.017	61.70***
FDAX	-0.065	0.077	0.006	-0.016	0.000	-0.017	67.32***
ODAX1	-0.038	0.012	0.027	-0.003	-0.006	0.002	904.20***
ODAX2	-0.276	-0.017	-0.014	-0.003	-0.026	0.012	483.26***
ODAX3	-0.287	-0.020	-0.006	0.002	-0.024	0.003	521.27***
ODAX4	-0.491	0.028	0.014	-0.015	0.008	0.007	1506.04***
ODAX5	-0.408	-0.005	0.003	-0.007	-0.009	0.003	1035.75***
ODAX6	-0.413	-0.022	0.008	0.006	-0.013	-0.006	1068.04***

(table cont'd.)

Panel C: Thirty Minute Return							
	Autocorrelation at						Ljung-Box χ^2
Securities	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	
DAX	0.118	0.023	-0.043	-0.004	0.004	0.005	51.10***
FDAX	0.063	-0.018	-0.027	0.013	-0.010	0.001	16.51
ODAX1	-0.259	0.033	-0.018	0.003	-0.011	0.004	213.03***
ODAX2	-0.261	-0.004	-0.037	0.027	0.001	-0.016	219.67***
ODAX3	-0.263	0.042	-0.049	0.015	0.003	-0.004	229.26***
ODAX4	-0.429	-0.004	0.008	0.021	-0.014	-0.038	579.83***
ODAX5	-0.361	-0.041	-0.009	0.037	-0.011	-0.034	419.12***
ODAX6	-0.388	-0.014	-0.009	0.030	-0.021	-0.003	474.34***

*** Significant at 0.1%

The ODAX1 is the call ODAX estimated from implied volatility using trades in the past 15 minutes, ODAX2 is the call ODAX estimated from implied volatility using trades in the past hour, ODAX3 is the call ODAX estimated from implied volatility using trades in the past day, ODAX4 is the put ODAX estimated from implied volatility using trades in the past 15 minutes, ODAX5 is the put ODAX estimated from implied volatility using trades in the past hour, ODAX6 is the put ODAX estimated from implied volatility using trades in the past day.

interesting points are observed here. First, the first-order autocorrelations are negative for the ODAX contracts. One possible reason is the effect of bouncing between the bid and the ask prices. However, this will remain to be a speculation due to the lack of data on the bid and ask prices. Besides, the positive first order autocorrelation of the DAX returns suggests that prices are "sticky" for the DAX due to infrequent trading.[6] Second, the first-order autocorrelation for puts is larger than that for calls. This finding, together with the descriptive statistics discussed earlier, shows that puts and calls exhibit different intraday characteristics. Third, the first-order autocorrelation is much smaller for the FDAX than those of DAX and ODAX. It means that the futures market is more efficient than the options and spot market in the sense past returns have little correlation relationship with the current one. Fourth, the first-order autocorrelation is much larger than those of higher orders. For example, the first order autocorrelation of the five minute returns of ODAX1 (call ODAX with trades in past fifteen minutes to calculate the implied volatility) is -0.225, which is much larger than that of the second-order autocorrelation, -0.058. Though the Ljung-Box statistics are significant, the small magnitudes of higher order autocorrelation coefficients are not economically significant. This shows that the markets are quite efficient in the sense that intraday returns are virtually uncorrelated over a longer time span.

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6 Trading of individual DAX stocks is not frequent. Nevertheless, the DAX is updated every minute. If no trading occurs during the minute, the DTB will report the last reported DAX value as the current one and thus sticky prices.

2.4.2 Autoregressive Conditional Heteroscedasticity (ARCH) Effects

The ARCH model is first proposed by Engle (1982) and generalized by Bollerslev (1986) into the Generalized ARCH (GARCH) models. ARCH / GARCH models allow the conditional variance to change over time. A simple ARCH(M) model posits that the variance to follow an autoregressive process of order M (an AR(M) process).

To test for the presence of any ARCH effects, two tests are employed: the Portmanteau Q-test and Engle's (1982) Langrange Multiplier (LM) tests. Since the intraday returns of the DAX securities exhibit strong first-order autocorrelation, they are modeled as the following first order autoregressive (AR(1)) process:

$$R_{j,t} = \alpha + R_{j,t-1} + v_t, \tag{2.2}$$

where $R_{j,t}$ is the return of security j (j = DAX, FDAX and ODAX) at time t and v_t is the error term. Residuals of (2.2), v_t, are tested for the ARCH effects. Apart from testing ARCH effects on the residuals of (2.2), the return itself, $R_{j,t}$, is also tested for ARCH effects by the Q and LM tests.

Tables 2.5 and 2.6 show the Q- and LM statistics for testing for the presence of ARCH effects in v_t of model (2.2) and the raw series under different data collection procedures. Both the Q statistics and the LM statistics are significant for order one to four for all the three DAX securities under the three different intraday return series. That means, there exist ARCH effects. The existence of ARCH effects also makes it appropriate to apply ARCH types of models to model the conditional variance of the

Table 2.5

Testing of ARCH Effects for Residuals of Model (2.2)

Panel A: Five Minute Return

	Q-Test Statistics				LM-Test Statistics			
Contract	Order 1	Order 2	Order 3	Order 4	Order 1	Order 2	Order 3	Order 4
DAX	238.93	247.55	258.21	263.43	239.20	240.52	248.51	251.23
FDAX	358.27	621.54	924.94	1218.79	362.43	551.30	737.85	881.54
ODAX1	142.34	201.86	259.97	306.21	143.36	189.61	230.95	258.99
ODAX2	171.44	195.05	234.98	268.21	172.17	185.42	216.13	236.95
ODAX3	167.67	207.98	290.52	347.11	168.53	195.63	260.25	293.58
ODAX4	197.41	463.41	701.22	849.81	200.10	426.94	586.61	652.99
ODAX5	277.53	629.74	812.88	984.15	280.46	567.43	659.34	733.21
ODAX6	374.35	626.07	801.16	936.73	378.07	554.71	643.66	698.59

Panel B: Fifteen Minute Return

	Q-Test Statistics				LM-Test Statistics			
Contract	Order 1	Order 2	Order 3	Order 4	Order 1	Order 2	Order 3	Order 4
DAX	134.24	213.75	279.33	332.18	141.98	202.74	239.66	264.57
FDAX	280.60	333.58	358.21	444.99	287.15	301.30	313.86	379.02
ODAX1	188.50	242.24	332.90	448.43	207.40	235.25	292.81	356.23
ODAX2	156.13	202.50	367.80	513.02	166.25	191.30	323.57	397.06
ODAX3	230.48	317.19	488.76	707.01	244.31	290.37	407.11	522.01
ODAX4	49.75	107.85	159.56	199.37	51.71	108.92	146.60	170.61
ODAX5	50.42	120.04	156.68	198.98	52.27	119.29	143.21	171.74
ODAX6	49.82	123.09	158.52	208.11	52.19	122.68	145.94	177.84

(table cont'd.)

Panel C: Thirty Minute Return								
	Q-Test Statistics				LM-Test Statistics			
Contract	Order 1	Order 2	Order 3	Order 4	Order 1	Order 2	Order 3	Order 4
DAX	23.05	26.07	32.10	39.27	26.36	28.49	34.24	42.76
FDAX	79.75	84.85	90.94	99.91	87.44	88.04	92.38	103.42
ODAX1	36.55	105.55	144.25	198.30	43.56	111.29	135.15	174.38
ODAX2	32.76	82.42	116.91	145.86	36.37	83.24	105.22	130.44
ODAX3	65.88	134.58	180.04	214.99	75.16	134.52	155.03	173.25
ODAX4	7.38*	18.50	20.66	32.90	8.34**	20.61	22.20	35.53
ODAX5	14.36	21.74	23.74	30.20	15.59	23.09	24.58	32.57
ODAX6	17.32	36.35	47.63	52.47	19.06	39.87	49.74	52.07

** Significant at 0.5%
* Significant at 1%

Note: All test statistics are significant at 0.1%, up to 12 lags, except those marked with asterisks. The Q-Test statistics is the Portmanteau Q statistics; the LM test statistics are suggested in Engle (1982). The model estimated is: an AR(1) in the form of $R_{j,t} = \alpha R_{j,t-1} + v_t$, where j=DAX, FDAX and ODAX. ODAX1 is the call ODAX estimated from implied volatility using trades in the past 15 minutes, ODAX2 is the call ODAX estimated from implied volatility using trades in the past hour, ODAX3 is the call ODAX estimated from implied volatility using trades in the past day, ODAX4 is the put ODAX estimated from implied volatility using trades in the past 15 minutes, ODAX5 is the put ODAX estimated from implied volatility using trades in the past hour, ODAX6 is the put ODAX estimated from implied volatility using trades in the past day.

Table 2.6

Test of ARCH Effects in Return of the DAX Securities

Panel A: Five Minute Return								
	Q-Test Statistics				LM-Test Statistics			
Contract	Order 1	Order 2	Order 3	Order 4	Order 1	Order 2	Order 3	Order 4
DAX	38.95	50.39	60.84	67.36	39.00	48.59	57.28	62.17
FDAX	387.16	651.69	948.95	1247.27	391.67	575.93	753.87	898.71
ODAX1	142.90	209.64	261.22	304.33	144.44	197.09	232.05	257.96
ODAX2	147.63	182.05	219.29	260.23	148.66	172.20	199.14	226.80
ODAX3	163.08	220.13	295.47	363.74	164.93	207.38	262.42	304.88
ODAX4	546.49	728.06	939.52	1088.59	552.34	644.31	765.29	820.53
ODAX5	713.36	973.82	1195.96	1366.16	720.30	842.80	943.22	1000.42
ODAX6	684.91	892.83	1106.32	1279.69	690.81	781.12	888.96	952.45

Panel B: Fifteen Minute Return								
	Q-Test Statistics				LM Test Statistics			
Contract	Order 1	Order 2	Order 3	Order 4	Order 1	Order 2	Order 3	Order 4
DAX	136.33	214.16	280.44	332.86	143.78	202.28	239.84	264.32
FDAX	328.09	379.39	401.83	485.61	335.59	344.54	356.15	418.77
ODAX1	347.46	397.59	471.42	619.87	389.14	397.92	438.40	520.82
ODAX2	245.35	278.13	449.03	640.06	261.98	268.96	412.68	500.80
ODAX3	344.66	385.32	557.74	868.04	364.82	368.58	512.48	674.41
ODAX4	484.67	546.70	584.68	639.98	513.76	517.71	531.85	559.74
ODAX5	256.34	333.26	369.16	420.64	269.11	306.07	316.97	346.78
ODAX6	399.50	366.61	399.36	455.14	317.96	341.59	351.79	383.72

(table cont'd.)

Panel C: Thirty Minute Return								
	Q-Test Statistics				LM-Test Statistics			
Contract	Order 1	Order 2	Order 3	Order 4	Order 1	Order 2	Order 3	Order 4
DAX	22.10	25.38	30.83	39.15	25.19	27.62	32.63	43.13
FDAX	67.86	73.50	79.50	88.81	74.23	75.60	79.65	91.64
ODAX1	103.37	188.03	248.80	306.40	131.49	197.05	226.01	254.85
ODAX2	76.11	133.56	179.40	220.33	87.92	132.69	157.16	189.46
ODAX3	142.98	229.24	288.13	339.01	175.47	232.62	249.70	272.66
ODAX4	73.80	76.90	79.22	90.99	86.82	87.14	88.86	99.81
ODAX5	50.67	56.00	56.79	64.50	56.68	59.61	59.81	69.67
ODAX6	107.25	121.54	130.40	137.07	124.27	129.38	133.97	136.46

Note: All test statistics are significant at 0.1%, up to 12 lags. The Q-Test statistics is the Portmanteau Q statistics; the LM test statistics are suggested in Engle (1982). ODAX1 is the call ODAX estimated from implied volatility using trades in the past 15 minutes, ODAX2 is the call ODAX estimated from implied volatility using trades in the past hour, ODAX3 is the call ODAX estimated from implied volatility using trades in the past day, ODAX4 is the put ODAX estimated from implied volatility using trades in the past 15 minutes, ODAX5 is the put ODAX estimated from implied volatility using trades in the past hour, ODAX6 is the put ODAX estimated from implied volatility using trades in the past day.

error terms. Thus, it gives the "green light" to employ EGARCH model in the study of volatility spillovers among the DAX securities.

2.4.3 Contempaneous Correlations of Return and Return Squares

Table 2.7 shows the contempaneous correlation of the return of the DAX securities. All the correlation coefficients are significant at 0.1%. There are several important observations here. First, the correlation between DAX and FDAX is much higher than that between DAX and ODAX and that between FDAX and ODAX. This shows that the DAX and FDAX are more closely related with each other; while the ODAX appears to be relatively unimportant in the system. Second, the correlations among the three securities become much stronger if a larger time grid is used. This result is consistent with the notion that much noise will be in the data should a short time grid is used. Third, the correlation between calls and puts is very low. This correlation is even lower than those between DAX and ODAX or between FDAX and ODAX; although puts and calls are tied together through the put-call parity. This finding is also consistent with earlier conjectures that puts and calls exhibit different intraday return patterns.

The squares of return are used as the proxies for variances, hence volatilities, of contempaneous returns of the DAX securities. Correlation of the squares of return is given in Table 2.8. The analysis in general is qualitatively the same as those of correlation of returns.

Table 2.7

Correlation Matrix of Returns of DAX securities

Panel A: Five Minute Returns

	DAX	FDAX	ODAX1	ODAX2	ODAX3	ODAX4	ODAX5
FDAX	0.5178						
ODAX1	0.2127	0.1881					
ODAX2	0.2407	0.2027	0.8730				
ODAX3	0.2447	0.2112	0.8357	0.8873			
ODAX4	0.1344	0.1083	0.0743	0.0707	0.0764		
ODAX5	0.1443	0.1148	0.0691	0.0783	0.0812	0.9335	
ODAX6	0.1496	0.1146	0.0761	0.0837	0.0845	0.9126	0.9512

Panel B: Fifteen Minute Returns

	DAX	FDAX	ODAX1	ODAX2	ODAX3	ODAX4	ODAX5
FDAX	0.7304						
ODAX1	0.3486	0.3564					
ODAX2	0.4327	0.4117	0.7927				
ODAX3	0.4693	0.4504	0.7816	0.8713			
ODAX4	0.2453	0.2400	0.1295	0.1296	0.1503		
ODAX5	0.2921	0.2744	0.1288	0.1642	0.1771	0.8824	
ODAX6	0.3037	0.2764	0.1384	0.1674	0.1888	0.8812	0.9510

(table cont'd.)

Panel C: Thirty Minute Returns							
	DAX	FDAX	ODAX1	ODAX2	ODAX3	ODAX4	ODAX5
FDAX	0.8168						
ODAX1	0.4891	0.4981					
ODAX2	0.5260	0.5420	0.7674				
ODAX3	0.5864	0.6023	0.8010	0.8592			
ODAX4	0.3374	0.3419	0.2118	0.1962	0.2170		
ODAX5	0.3828	0.3844	0.2065	0.2527	0.2667	0.8497	
ODAX6	0.4079	0.4041	0.2293	0.2587	0.2866	0.8687	0.9307

All correlations are significant at 0.1%.

ODAX1 is the call ODAX estimated from implied volatility using trades in the past 15 minutes, ODAX2 is the call ODAX estimated from implied volatility using trades in the past hour, ODAX3 is the call ODAX estimated from implied volatility using trades in the past day, ODAX4 is the put ODAX estimated from implied volatility using trades in the past 15 minutes, ODAX5 is the put ODAX estimated from implied volatility using trades in the past hour, ODAX6 is the put ODAX estimated from implied volatility using trades in the past day.

Table 2.8

Correlation Matrix of Squares of Returns of DAX securities

Panel A: Five Minute Return Squares

	DAX	FDAX	ODAX1	ODAX2	ODAX3	ODAX4	ODAX5
FDAX	0.1405						
ODAX1	0.1648	0.0691					
ODAX2	0.1722	0.0732	0.8889				
ODAX3	0.1447	0.0747	0.8422	0.8992			
ODAX4	0.0802	0.0708	0.1282	0.1255	0.1083		
ODAX5	0.0884	0.0720	0.1356	0.1458	0.1251	0.8622	
ODAX6	0.1226	0.0686	0.1798	0.1856	0.1735	0.8059	0.8803

Panel B: Fifteen Minute Return Squares

	DAX	FDAX	ODAX1	ODAX2	ODAX3	ODAX4	ODAX5
FDAX	0.4897						
ODAX1	0.2111	0.1849					
ODAX2	0.2571	0.2277	0.6857				
ODAX3	0.3295	0.2803	0.6759	0.7779			
ODAX4	0.1338	0.1041	0.1159	0.1274	0.1333		
ODAX5	0.1575	0.1429	0.1196	0.2009	0.1639	0.7660	
ODAX6	0.1622	0.1368	0.1270	0.1611	0.1784	0.7696	0.9011

(table cont'd.)

Panel C: Thirty Minute Return Squares							
	DAX	FDAX	ODAX1	ODAX2	ODAX3	ODAX4	ODAX5
FDAX	0.6888						
ODAX1	0.3578	0.4017					
ODAX2	0.3221	0.3394	0.6929				
ODAX3	0.4629	0.4896	0.7353	0.7521			
ODAX4	0.2353	0.2747	0.2168	0.1648	0.2034		
ODAX5	0.2853	0.3404	0.2203	0.2302	0.2505	0.7170	
ODAX6	0.2746	0.3231	0.2312	0.2035	0.2791	0.7457	0.8522

All correlations are significant at 0.1%.

ODAX1 is the call ODAX estimated from implied volatility using trades in the past 15 minutes, ODAX2 is the call ODAX estimated from implied volatility using trades in the past hour, ODAX3 is the call ODAX estimated from implied volatility using trades in the past day, ODAX4 is the put ODAX estimated from implied volatility using trades in the past 15 minutes, ODAX5 is the put ODAX estimated from implied volatility using trades in the past hour, ODAX6 is the put ODAX estimated from implied volatility using trades in the past day.

2.5 Summary

In this chapter, intraday returns of the DAX securities are analyzed. This analysis gives a basic understanding of the intraday behaviors of the returns of the index securities. It is found that intraday returns exhibit strong non-normality and ARCH effects. An important observation is that returns of calls and puts have different intraday behaviors. This gives support to separate puts and calls into further analysis.

Chapter 3

Intraday Price Discovery in Index Securities: Evidence From The German Markets

3.1 Introduction

This chapter discusses the price discovery process among the DAX securities. Price discovery is the process whereby markets attempt to find equilibrium prices for securities. For example, Booth, Lin, Martikainen and Tse (1996) study the price discovery process between upstairs and downstairs markets, Lin and Rozeff (1995) investigate the price discovery between ordinary stock and convertible preferred stocks. Harris, McInish, Shoesmith and Wood (1995) study the contribution of price discovery of IBM among different stock exchanges. Hasbrouck (1995) examines the degree of contribution to price discovery when the same security is traded on more than one location. When the same or similar securities are traded across different markets, price discovery will occur in the least cost market, because of lower cost can profit the information.[1]

Previous work in price discovery involving index derivatives mainly focuses on the bivariate lead-lag relationships between the stock index and index futures or between stock index and index options (e.g., Chan (1993) and Bhattcharya (1987)). This study differs from previous work principally in two ways. First, rather than examining the pricing relationships within a bivariate framework, this dissertation studies the pricing

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1 Alternatively, Admati and Pfleiderer (1988) show that informed traders will trade more actively in periods when liquidity trading is concentrated and prices in those periods are more infomative. Thus, price discovery may also occur in markets where trading is concentrated.

relationships in a multivariate setting by including three index securities (stock index, index futures and index options) into the analysis. Second, instead of a mere replication of previous work in lead-lag relationships, this chapter also examines the degree of information sharing. The primary contribution of this chapter is to provide further empirical evidence of the intraday price discovery process when three index securities are involved.

3.2 Literature Review

Early work in price discovery concentrates on differences in the efficiencies of information processing among different securities markets. When a security or similar securities are traded in multiple locations, the differences in efficiencies of information processing across markets may be the result of trading costs or broker inducements.

In the study of price discovery in equity markets, Garbade and Silber (1979) investigate securities traded on the New York Stock Exchange (NYSE), the Midwest Stock Exchange (MWSE) and the Pacific Stock Exchange (PSE) and determine where does price discovery take place. Using variances of prices as the proxies for information, they find that the NYSE remains to be the leader exchange in information processing, and the MWSE and the PSE are "satellite exchanges." However, one important point is that these satellite exchanges are not 100% satellites. Information provided by trades through the two regional markets will also be incorporated in trades executed at the NYSE.

More recently, several papers readdress the issue of price discovery among equity markets by more advanced econometric techniques. Harris et al. (1995) reexamine the

price discovery process of IBM across the NYSE, the MWSE and the PSE through cointegration and error correction models. They find that the NYSE is the dominant stock exchange in information processing, but the regional stock exchanges also feedback information to the NYSE. In other words, their findings are consistent with those in Garbade and Silber (1979).

Hasbrouck (1995) studies price discovery through information sharing. Using a Bayesian approach, he shows that the information share in NYSE is more than 90%. Although other regional stock exchanges are subordinate to the NYSE in information processing, they are not mere price takers. Information occurs at these regional exchanges will also affect the prices at the NYSE.

Booth, Lin, Martikainen and Tse (1996) examine price discovery between upstairs and downstairs transactions in the Finnish stock market. Using error correction and information sharing models, they conclude that price discovery occurs at the downstairs market. The upstairs market is for liquidity purposes, giving an economic rationale for the coexistence of these two parallel markets.

To sum up, despite the differences in econometric techniques and datasets, the same conclusion in previous work is reached - markets do not play equal roles in information processing, hence they have different roles in the price discovery process even though the security is the same. It leads to the question whether similar securities have the same contributions or which roles do they play in the price discovery process.

Price discovery is not restricted to the "One Security, Many Markets" scenario. The basic idea is being extended to the study of price discovery among similar securities,

for example, Lin and Rozeff (1995) study the price discovery process in ordinary and convertible preferred stocks. Specifically in price discovery among derivatives, there is an extant literature in the examination of the lead-lag relationships between futures and spot prices or between spot and option prices.

There is evidence which suggests that futures markets tend to lead the spot market. Zechauser and Niederhoffer (1983) show that the closing basis (difference between closing prices of futures and spot index) contains information for future spot movements. Finnerty and Park (1987) show that stock index futures prices changes are correlated with the stock index cash price changes. Kawaller, Koch and Koch (1987) find that Standard & Poor 500 (S&P 500) futures price movements consistent lead the S&P 500 index by 20 to 45 minutes. Herbst, McCormack and West (1987) study intraday lead-lag relationship between index futures and the stock index. They also find that index futures tend to lead the spot market. However, the stock index reacts very quickly to movements in futures prices (less than one minute) and trading strategies based on forecasting spot movements from futures prices would not be profitable.

Stoll and Whaley (1990) find that lead-lag relationship between stock index and index futures is not unidirectional. Using transaction data of the S&P 500 futures and S&P 500 index for the period April 21, 1982 to March 31, 1987, they show that price changes in futures tend to lead price changes in the S&P 500 index. The average lead time is five minutes, but occasionally it can be ten minutes or longer. However, this lead-lag relationship is not completely unidirectional though the lead-lag effect becomes smaller when the futures market becomes more mature. Their evidence suggests that

price discovery occurs in the futures market, in which new market information is disseminated before the stock market. Furthermore, they also show that the lead-lag relationship between returns of the S&P 500 index and the returns of the futures has tightened over time, which means a growing integration between the two markets.

Kawaller, Koch and Koch (1993) find that there is substantive contemporaneous price relation between the S&P 500 futures prices and the S&P 500 index. Their results indicate that the measures of contemporaneous feedback are positively associated with the daily ranges of the futures prices. They assert that the relation between cash and futures prices becomes stronger as volatility of futures prices increases. As volatility increases, information is being impounded at a faster rate so that the relation between cash and futures prices become stronger.

Ross (1989) put forward the information-volatility hypothesis.[2] According to this hypothesis, higher volatility will mean higher information flow. If index futures tend to lead the stock index, then the volatility of futures markets should be higher than that of the spot market. It is because information-induced tradings in the futures market will produce greater volatility in the futures markets. Consistent with Ross's hypothesis, Whaley (1986), Kawaller, Koch and Koch (1990), MacKinlay and Ramaswamy (1988)

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[2] More detailed discussion of intraday volatility is given in Chapter 4. Discussions here highlight the relationships in information processing among the index securities.

and Chu and Bubnys (1990) show that intraday volatility of S&P 500 futures prices exceed that of the S&P 500 index.[3]

Thus, previous work show that futures market embeds higher information flow, hence futures markets are more efficient in information processing than the spot market. The higher efficiency in information processing is attributable to lower trading costs in futures markets. Moreover, the pricing relationship is not a simple case in which futures lead the spot. The feedbacks are both bidirectional and contemporaneous.

Recently, more advanced time series techniques like cointegration analysis are applied in the study of the lead-lag relationships between the spot and futures markets. Two time series are said to be cointegrated if the individual series are not stationary (integrated of the same order) but a linear combination of the two series is stationary (i.e., I(0)). Economically, cointegration means that one series is useful in anticipating another and a long run equilibrium relationship between the two time series exists although individual series is a random process.

Ghosh (1993) finds contemporary cointegration in the S&P 500 and the Commodity Research Bureau (CRB) spot and futures markets. Cointegration between contemporaneous spot and futures markets implies that prices in one market will be helpful in forecasting the price of another market. That means, both systems exhibit a stable long run equilibrium relationship. Spot (futures) prices provide useful information in predicting the prices of futures contracts (spot index). Wang and Yau (1994) study

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[3] Alternatively, this may also be interpreted as a mere "over reactions" in the futures markets.

the linkage between the S&P 500 index futures and the spot S&P 500 index through cointegration. They find that both the spot and futures markets are linked together. Thus, empirical evidence so far tends to suggest the existence of cointegration relationship between stock index and index futures markets. Finding cointegration implies a long run equilibrium relationship between the spot and futures markets. This point will be discussed in greater details in the section on Method of Analysis.

Empirical work using options in the study of the price discovery process are far fewer than those using futures. One reason is that though options are also standardized contracts, they have more variations in contract specifications (different exercise prices and maturities, calls and puts) than the futures. Thus, there is the selection problem - the problem of deciding which option contract to use. Another reason is the infrequent trading problem. Liquidity of option markets is not as high as that of futures market. The limited amount of empirical work of using options in the study of price discovery, however, produces mixed results.

Manaster and Rendleman (1982) are one early work in the study of price discovery between the spot and option markets. They argue that investors may regard options to be superior investment vehicles due to lower trading costs, fewer restrictions in short sales and the lower margin requirement (leverage effects). Because of these advantages, an informed investor will tend to trade in the options market. In this way, option prices will contain information about future movements of the spot market. Empirically, they use implied option prices to show that option prices provide future information about the spot market. However, Manaster and Rendleman (1982) only use

daily data and the stock market closes 10 minutes earlier than the options market. The apparent information embedded in option prices may reflect more recent rather than better information because the spot market is closed while the options market is still open. Thus, there is a problem of simultaneity in using daily data. This problem of simultaneity can be mitigated by the intraday transaction data employed in this study.

Kumar, Sarin and Shastri (1992), however, find that returns on equity options are related to lagged and contemporaneous returns of the underlying stocks. It takes the option market a hour to adjust to new equilibrium prices after a block trade while the equity market only takes fifteen mainutes. In this way, the cash market is more efficient in reacting to new information. The abnormal price behavior of equity options after a block trade also shows that the stock market leads the options market in adjusting new equilibrium prices. Therefore, the options market may not be as efficient as the stock market in processing new information. One important point, however, is that equity options are not as heavily traded as the underlying stocks. The inferiority of equity options in information processing may be a by-product of low liquidity in the equity options market. Low liquidity will mean higher overall trading costs (time to search for contracting parties, wider bid/ask spreads, price impacts of large orders, etc.); thus, findings in Kumar et al. (1992) are also consistent with the conjectures that price discovery will occur in the least cost market.

In a recent paper, Fleming, Ostdiek and Whaley (1996) (FOW) study the price discovery process between the stock index, index futures and index options.[4] Their trading cost hypothesis predicts that the market with the lowest overall trading costs will react most quickly to new information. It is because traders with valuable private information will try to transact in the market of lowest transaction costs so that they can maximize profits on their private information. Since futures markets have the lowest overall trading costs and the spot market has the highest overall trading costs, the trading cost hypothesis predicts that futures lead options and options lead the spot index.

To test for the lead-lag relationship between the derivatives and the stock index, hence their trading cost hypothesis, they use the following model:

$$R_{j,t} = \alpha + \sum_{m=-4}^{4} \beta_m R_{k,t+m} + \epsilon_t . \tag{3.1}$$

In the above model, $R_{j,t}$ are returns of stock index and index options at time t, $R_{k,t}$ are returns of index futures and index option returns at time t, in which $j \neq k$. The above model is known as the Sims Approach to causality. Their findings show that returns of index futures and index option lead the return of the stock market, and returns of index futures lead the returns of index options. Thus, the trading cost hypothesis posited in FOW has some empirical support. Three comments about their method are made here. First, the Sims approach to causality is more a statistical concept than an intuitively appealing technique. From an investor's point of view, equation (3.1) will have little value in terms of forecasting. It is because future values, as well as past values, of the

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4 As put forward in FOW, their study is the first one to include stock index, index futures and index options in the price discovery process.

returns of other securities are included. It is difficult to think intuitively of incorporating unobservable future returns of other securities into the prediction model. The use of Granger Causality (to be discussed in greater detail in the section on Method of Analysis), which does not include future values of securities return in the lead-lag relationship, is a more reasonable approach to use. Second, the analysis in FOW is still within a bivariate framework. Though three securities are considered, the pair-wise analyses isolate the interaction effects of the security not in the model. Third, FOW use returns of the index (options) as the dependent variable and returns of the futures and options as the independent variables in equation (3.1). Though they find that futures lead options and options lead the spot, the roles of the returns of the cash market in the causal relationship of returns of futures and options are completely ignored. From a price discovery perspective, their analyses are not complete.

Another piece of evidence that supports the trading cost hypothesis, however, shows that the stock market leads the options market. Stephan and Whaley (1990) show that it is more cost efficient to enter a trade in the stock market than in the equity options market. They investigate the intraday relationships between price changes and trading volume of options and equities. Using a sample of CBOE actively traded call options, they show that price changes in the stock market lead price changes in the option market by about fifteen minutes. Furthermore, stock market also leads the option market in terms of trading activities. Thus, this evidence is consistent with the findings of Kumar et al. (1992) that equity market leads stock options because of lower transaction costs.

Based on previous findings, therefore, there are reasons to believe that if investors have valuable private information, they will tend to trade in markets with overall lowest transaction costs. The lower the transaction costs, the more profitable the information will be.

Previous work on price discovery between the stock index and index futures in Germany (the DAX and the FDAX respectively) can be found in Grunbichler, Longstaff and Schwartz (1994) (GLS) and Broussard, Booth and Loistl (1997) (BBL). Using different statistical techniques, both studies conclude that the FDAX leads the DAX. In other words, the FDAX is more efficient in information processing than the DAX. Although both studies reach the same conclusion, they attribute this for different reasons. GLS argue that the electronic trading system of the German future exchange contributes to more efficient information processing than the floor trading of the Frankfurt Stock Exchange. BBL, however, argue that the superiority of the FDAX is asset type.[5]

From the above discussion, there is a consensus that price discovery tends to occur in the least cost market. From this perspective, stock derivatives should lead the stock index. Futures tend to lead the cash market; but mixed results are obtained for the options market. However, one thing to bear in mind is that individual equity options have greater nonsynchronous trading problems than index options. The apparent conflict in evidence is just a manifestation of the trading cost argument.

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[5] BBL point out that GLS completely ignore a parallel electronic trading system, the Integrietes Börsenhandels - und Informations - System, the IBIS. Hence, the conclusion that the electronic system is more efficient is suspect.

As discussed earlier, FOW is the first piece of work that directly addresses the roles of stock index, index futures and index options together in the price discovery process. They study the price discovery process within a lead-lag relationship framework but the relative importance of each security in information processing is ignored. Lead-lag relationships between derivatives and the spot market only reveal which securities are more efficient in information processing. Previous evidence only answers the question of whether derivatives process information more efficiently than the spot market. The basic question of how efficient are the derivatives in information processing, i.e., the relative efficiencies of the derivatives over the spot market, is left out.

This chapter differs from existing literature in several aspects. First, the price discovery process is explored through the pricing relationships of the three DAX securities (the DAX, the FDAX and index options, the ODAX) together instead of just two of the index securities in a bivariate framework. Second, the techniques employed are different. Apart from the standard Vector Autoregression (VAR) and Granger causality techniques, this dissertation also looks at the relative importance of the index securities in information processing through the Gonzalo and Granger information sharing model.

3.3 Data

3.3.1 Data Sources

Daily transaction data of the FDAX and ODAX are obtained from the German Futures and Options Exchange, the Deutsche Terminbörse (DTB). The FDAX and ODAX transaction data contain the ticker symbol, types of security, exercise price,

expiration date, day of transaction, transaction time, transaction prices and trading volume. Note that the transaction time is recorded up the nearest hundredth of a second. Data on the DAX are obtained from the Frankfurt Stock Exchange (FSE). When the FSE opens, the DAX will be reported as long as the first trade in the DAX stocks occurs. The DAX is reported up to two decimal places and is updated every minute. Transaction time of the DAX is recorded at the nearest second, which is the same for each day. For example, if the first DAX observation is at 10:33:24, the DAX is reported at 10:34:34 and so on throughout the same day. The second is determined by trades in the constituent DAX stocks. Table 1.1 gives the sample content of the data. For the FDAX and ODAX data, they cover the period January 1992 to August 1994. Table 3.1 shows the distribution of trading volumes of each FDAX contract in the sample. For the DAX data, however, they only cover up to March 1994. Therefore, the sample period of this study is restricted to January 1992 to March 1994 due to data availability.

3.3.2 Prices of the DAX Securities

The underlying asset of index derivatives is the stock index. For the information sharing models to work, constructing relevant price series of the index securities is necessary. For the DAX and the FDAX, it is not a big problem since the DAX is reported every minute and prices of nearby FDAX can be used. Finding the price series of the ODAX, however, is not that straight forward. As put forward in Chapter 2, there are the selection and infrequent trading problems if a particular ODAX contract is

Table 3.1

Distribution of Trading Volume of Each FDAX Contract For the Period January 1, 92 to August 31, 1994

Contract	Number of Trades	Maximum Volume	Minimum Volume	Average Volume Per Trade
Mar 92	65,807	1,000	1	7.0949
Jun 92	64,505	1,000	1	8.6100
Sep 92	122,477	1,000	1	9.4214
Dec 92	119,307	2,000	1	8.1738
Mar 93	104,994	1,194	1	8.0406
Jun 93	90,472	800	1	8.3198
Sep 93	138,498	1,500	1	8.0300
Dec 93	158,867	5,063	1	7.4833
Mar 94	227,439	1,782	1	6.7288
Jun 94	185,282	1,500	1	6.9693
Sep 94	168,782	957	1	6.1750
Dec 94	2,445	539	1	7.5337
Mar 95	247	200	1	11.0486

Volume represents the number of FDAX contracts traded per trade. Note that the Jun 94, Sep 94, Dec 94 and Mar 95 contracts have not expired by the time of study.

chosen. Instead of using the prices of a particular ODAX contract, this study follows the FOW's approach in implying the DAX from ODAX prices.

Principally, there are two ways to imply the DAX from ODAX prices. The first one is the use of an equilibrium model and the second one is the use of put-call parity.

Put-call parity considers a no arbitrage condition but not any equilibrium option pricing model.[6] Let $P(S_j,k)$ be the price of a European put with exercise price k, the underlying asset be j, $p(S_j,k)$ be the price of a European call with exercise price k, S_j be the price of the underlying asset and r_f is the risk-free rate. Put-call parity is stated as:

$$P(S_j,k) = k/(1+r_f) - S_j + p(S_j,k) \ . \tag{3.2}$$

If the prices of the put and the call options and the risk-free rates are known, the cash index can then be "implied" by (3.2).

To imply the DAX from ODAX contracts via the put-call parity, a matched trade of puts and calls is needed. A matched trade is one that consists of a put and a call that have the same maturity and the same exercise price. Given the risk-free rate, (3.2) can be applied to find the implied value of the DAX.

Though the problem of finding the implied DAX can be solved by using the put-call parity, there is still the problem of simultaneity. The ODAX market is less liquid than the FDAX market. As a result, the numbers of matched trades will be very few. Table 3.2 shows the number of matched put-call transactions and the average time span

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6 Detailed proofs of the put-call parity can be found in Huang and Litzenberger (1988, Chapter 6).

Table 3.2

Number of Matched Put-Call Parity Pairs and Summary Statistics of the Span

		Time Span Between Matched Pairs			
Contracts	Number of Pairs	Mean	Std Dev	Minimum	Maximum
All	304,526	10.27	24.64	0.00	376.69
Jan 92	1,591	7.17	17.03	0.00	283.94
Feb 92	4,160	8.73	18.71	0.00	271.12
Mar 92	6,610	9.39	20.67	0.00	376.69
Apr 92	4,983	10.45	23.96	0.00	317.72
May 92	3,039	13.15	26.69	0.00	302.51
Jun 92	6,859	15.78	31.49	0.00	340.24
Jul 92	3,922	10.79	22.80	0.00	287.1
Aug 92	5,576	8.88	19.69	0.00	278.35
Sep 92	13,321	12.82	28.91	0.00	353.83
Oct 92	7,302	8.30	18.70	0.00	301.32
Nov 92	5,462	9.95	20.99	0.00	256.3
Dec 92	14,749	13.42	26.37	0.00	371.98
Jan 93	4,471	9.02	18.61	0.00	266.17
Feb 93	7,024	6.71	17.16	0.00	292.29
Mar 93	15,513	11.73	28.52	0.00	349.84
Apr 93	7,516	7.04	17.80	0.00	326.23
May 93	6,557	6.37	16.20	0.00	282.15
Jun 93	9,728	13.98	30.32	0.00	356.23
Jul 93	5,838	7.30	18.17	0.00	274.94
Aug 93	9,811	5.90	14.67	0.00	273.81
Sep 93	15,410	11.55	27.44	0.00	367.23
Oct 93	9,302	6.82	16.94	0.00	305.64
Nov 93	9,954	6.23	17.27	0.00	312.52
Dec 93	20,640	11.05	24.99	0.00	359.86
Jan 94	10,617	7.00	18.81	0.00	346.33
Feb 94	9,615	6.81	17.50	0.00	345.61
Mar 94	20,608	13.01	30.30	0.00	369.38

(table cont'd.)

Apr 94	8,932	6.50	16.96	0.00	342.91
May 94	7,751	6.51	18.37	0.00	347.76
Jun 94	18,250	12.61	30.21	0.00	373.09
Jul 94	8,981	6.37	17.17	0.00	317.02
Aug 94	8,632	6.78	18.40	0.00	335.38
Sep 94	9,206	16.51	33.27	0.00	351.29
Oct 94	787	25.19	42.23	0.00	303.55
Nov 94	25	64.71	53.35	0.04	185.75
Dec 94	1,618	38.88	49.31	0.00	359.89
Mar 95	166	64.55	67.28	0.11	317.47

The span is defined as the time (in minutes) between a matched put or call transactions. The matched transaction includes a put and a call option which have the same exercise prices and maturity. Note that the Sep 94, Oct 94, Nov 94, Dec 94, and Mar 95 contracts have not expired by the time of study.

between a matched trade. For all the 1,005,810 trades occurred between January 1992 and August 1994, there are 304,526 matched put-call trades.[7] The average span time between each matched trade is 10.27 minutes, and it can be as large as 6.28 hours. Note that if additional filter rules like restricting to nearby at-the-money options are used, the number of matched trades will be even fewer. When put-call parity is used to imply the index, there will be a broken series of implied index values. If past implied prices are substituted for the missing data, many zero returns will be generated. Then, the actual price discovery may occur within these "zero returns" but does not reflect in the option prices due to thin trading.

Another way to handle this problem of finding the implied index is to use Stephan and Whaley's (1990) approach. Since the index option is a derivative of the stock index, there exists a pricing relationship between the index option and the index:

$$O_t = f(S_t) \, , \tag{3.3}$$

where O_t is the price of the index option, S_t is the stock index and f(.) is the functional form. To find the stock index from the option prices, one can invert the right-hand side of (3.3) to yield:

$$f^{-1} \, (O_t) = S_t \, . \tag{3.4}$$

To allow for measurement errors, (3.4) can be rewritten as:

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7 Note that the sample period is only from January 1992 to March 1994, which means that the number of matched trades will be even smaller.

$$f^{-1}(O_t) = \hat{S}_t + \epsilon_t \ . \tag{3.5}$$

In Stephan and Whaley (1990), they compute the implied index price (S&P index) from the option prices through Roll's (1977) American option pricing model.

However, this approach will also encounter biases in implied prices due to problems in model specification and simultaneity. For example, the implied stock index will require an equilibrium model; however, there is still not a perfect model in option pricing. Stephan and Whaley (1990) argue that model selection is not a big problem, since the error term in (3.5) will capture the unexplained parts left by the model. Though model selection is not a big problem, there still exists the problem of simultaneity among the three index securities. This issue will be discussed further in the next subsection.

Since the ODAX is a European style option, this dissertation uses the Black-Scholes (1973) (B-S) model to imply the DAX. The B-S model for pricing European options of a non-dividend paying stock is:

$$\begin{aligned} C_t &= S_t\, N(d_1) - Xe^{-r\tau}N(d_2) \ , \\ P_t &= S_t \left[N(d_1) - 1\right] + Xe^{-r\tau}\left[1 - N(d_2)\right] , \end{aligned} \tag{3.6}$$

where C_t is the price of an European call at time t, P_t is the price of an European put at time t, N(.) is the cumulative normal distribution function; and

$$d_1 = \frac{\ln\left(\frac{S_t}{X}\right) + (r_f + 0.5\sigma^2)t}{\sigma\sqrt{t}}; \quad d_2 = d_1 - \sigma\sqrt{t}; \tag{3.7}$$

S_t is the stock price at time t, X is the exercise price, r_f is the three-month Euro-Mark rate, t is the fraction of a year to maturity and σ^2 is the variance of the return of the stock.[8] Note that the B-S option pricing model is for a stock that does not pay dividends. This point is very important since it is one of the main advantages of using the ODAX. Recall that the DAX is a "total performance" index by having the dividends reinvested. In this way, the DAX is indeed a "non-dividend paying stock" and there is no need to estimate its dividend yield as done in Stephan and Whaley (1990) and FOW.

In using the B-S option pricing model to imply the stock index, volatility of the return of the index (the variance, σ^2), has to be estimated. The implied volatility is the volatility that minimizes the deviations of actual prices and the estimated prices from the B-S model. Stephan and Whaley (1990) use the implied volatility at day t-1 to proxy for the implied volatility at day t. Implied volatility at day t-1 is estimated by using actual prices of options and values of other parameters at day t-1 in the B-S model. Fleming (1994) also shows that the best proxy for index return volatility on day t is the volatility rate implied by the preceding day's option prices. One problem with this method is that

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8 There are no short term government securities in Germany so the three-month Euro-Mark LIBOR (London Interbank Offer Rate) fixing is used as the proxy for the risk-free rate. LIBOR fixing is done daily at 11:00 a.m. (London time, i.e., noon German time) by averaging the offer rates of leading London banks on Euro-currencies deposits. The author is grateful to the Hong Kong Monetary Authority (HKMA) for supplying data on the three-month Euro-Mark LIBOR fixing.

the volatility is assumed to remain constant for the whole day. In other words, intraday volatility is ignored.

Modifying the method in Stephan and Whaley (1990), this dissertation breaks down the whole day into equal time intervals (in one hour and in 15-minute intervals). Volatilities implied by options prices within each time interval are then averaged out to find the implied volatility. The implied volatility is estimated via the B-S model for each at-the-money ODAX contract with a maturity of more than nine days and less than or equal to two months. Consistent with FOW, maturity of less than nine days are not used since the implied volatilities of these option contracts are much higher as they are going to expire. The implied volatility at time t-1 is used to proxy for the index return volatility at time t. Using this estimate of σ^2, the implied values of DAX can be found from the B-S model in equations (3.6) and (3.7).[9]

To ascertain that empirical results are not sensitive to different estimates of implied volatilities, implied DAX series are constructed by different estimates of implied volatilities. The first one uses implied volatility of trades in the past 15 minutes to estimate the DAX; the second one uses implied volatility of the past hour and the third one uses implied volatility of the previous day. In this dissertation, these option price series are labeled as ODAX1, ODAX2, ODAX3 respectively for the calls and ODAX4, ODAX5 and ODAX6 respectively for the puts.

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9 One additional filter rule is employed. The implied DAX must be within $\pm$ 20 index points of the current DAX. This filter aims to correct for reporting errors in the original database.

3.3.3 Correcting for Simultaneity

Since the DAX is updated every minute, it is appealing to construct minute-by-minute transaction series for the three DAX securities. The minute-by-minute series can be constructed by reporting the last transaction within the minute. If no trade occurs within the minute, then the price in previous minute is used. However, if the security is not actively traded, then such data series construction will produce a series of "sticky prices." Consequently, the actual price discovery may occur but fail to report due to infrequent trading.

One may argue that this is not a big problem given the FDAX contracts are actively traded. However, there is no guarantee that the FDAX contracts are traded in every minute. On the other hand, the DAX is updated every minute. This problem becomes more severe when we consider the ODAX, which is not as actively traded as the FDAX, even the implied values of the DAX are used.

To correct for the problem of nonsynchronous trading, this dissertation employs the REPLACE ALL and the MINSPAN approaches as put forward in Harris et al. (1995). The REPLACE ALL dataset is constructed as follows. Beginning at the start of each trading day, as soon as an observation is obtained for each DAX securities, the most recent trade for the other two is acquired to form the first matched trade. Equality of prices is not assumed. This matched pair is then saved and a new matched trade is formed in the same manner. The MINSPAN approach, however, will minimize the time span among trades of the three index securities.

To better understand these two approaches, it is easier to go through an example. Suppose we have a series of trades as follows:

Time	DAX	FDAX	ODAX
t=0	DAX_1	$FDAX_1$	
t=1	DAX_2		$ODAX_1$
t=2	DAX_3	$FDAX_2$	
t=3	DAX_4		$ODAX_2$
t=4	DAX_5	$FDAX_3$	$ODAX_3$

The time interval between t-1 and t is fixed. The REPLACE ALL approach constructs the first matched pair as (DAX_2, $FDAX_1$, $ODAX_1$). The second matched pair is (DAX_4, $FDAX_2$, $ODAX_2$) and the third one is (DAX_5, $FDAX_3$, $ODAX_3$). The MINSPAN approach has a natural stopping rule associated with the last security traded. The initial pair chosen is (DAX_2, $FDAX_1$, $ODAX_1$). Here the ODAX is the last security since the first trade of ODAX is the latest among the three securities. The MINSPAN further checks if a further trade in the DAX and the FDAX can reduce the time span. If so, the pair is updated. Back to this example, the first pair is (DAX_2, $FDAX_1$, $ODAX_1$) since the span between (DAX_2, $FDAX_1$, $ODAX_1$) and (DAX_3, $FDAX_2$, $ODAX_1$) are the same. The second pair is (DAX_3, $FDAX_2$, $ODAX_2$) and the third pair will be (DAX_5, $FDAX_3$, $ODAX_3$). One caveat, however, is that the numbers of matched trades under the REPLACE ALL and MINSPAN approaches are much smaller than that of simply using minute-by-minute returns.

Table 3.3 shows the descriptive statistics of the time span under different data collection procedures. The time span of using the REPLACE ALL and the MINSPAN procedures are rather small. The average time span for the MINSPAN procedure is around 25.50 seconds, while that of the REPLACE ALL procedure is around 30.10 seconds. When compared with the time span of using put-call parity (10.27 minutes), there is a huge improvement in correcting the problem of simultaneity. Note that using past 15 minute data to estimate implied volatility of the ODAX will always yield the highest number of observations. It is because only the first 15 minutes' data are lost due to estimation, while an hour and a day's data are lost in using past hour and past day data.

3.4 Method of Analysis

3.4.1 Granger Causality

Suppose we have two variables X and Y. If Y can help forecast X, it is said that Y Granger-causes X. More formally, Y Granger-causes X if

$$MSE\ [\hat{E}(X_{t+s}|X_t, X_{t-1}, \ldots)] > MSE\ [\hat{E}(X_{t+s}|X_t, \ldots, Y_t, Y_{t-1}, \ldots)]\ , \tag{3.8}$$

where MSE is the mean square error of forecast. Both bivariate and Multivariate Granger-causality tests are used to study the lead-lag relationships among the DAX derivatives.

The following Vector Autoregression (VAR) model is used to test whether the returns of derivatives Granger-causes that of the spot market:

$$Y_t = C + A'X_t + \epsilon_t\ , \tag{3.9}$$

Table 3.3

Data Collection Procedures and Time Span Between Each Matched Pair

Data Collection Procedure	No. of OBS.	Avg. TimeSpan (in seconds)	% of being first security in pair		
			DAX	FDAX	ODAX
MINSPAN (Call) - Past 15 Min	45070	25.59	36.96	26.66	36.42
MINSPAN (Call) - Past Hour	45050	25.59	36.97	26.66	36.41
MINSPAN (Call) - Past Day	44802	25.59	36.96	26.66	36.42
REPLACE ALL (Call) - Past 15 Min	46632	30.08	38.38	26.36	25.27
REPLACE ALL (Call) - Past Hour	46612	30.08	38.38	26.36	35.27
REPLACE ALL (Call) - Past Day	46356	30.08	38.39	26.35	35.27
MINSPAN (Put) - Past 15 Min	45299	25.49	37.02	26.63	36.39
MINSPAN (Put) - Past Hour	45302	25.50	37.02	26.64	36.38
MINSPAN (Put) - Past Day	45099	25.53	37.02	26.64	36.67
REPLACE ALL (Put) - Past 15 Min	46884	30.06	38.63	26.37	35.02
REPLACE ALL (Put) - Past Hour	46901	30.06	38.63	26.38	35.01
REPLACE ALL (Put) - Past Day	46688	30.09	38.60	26.38	35.04

Average time span is the average time span among the three index securities in each pair. MINSPAN and REPLACE ALL refer to the MINSPAN and REPLACE ALL approaches of forming pairs of DAX, FDAX and ODAX. The Call and Put inside the parentheses mean that whether calls or puts are used in forming the pairs. Past 15 Min means that implied volatility of ODAX are estimated by using previous 15 minutes ODAX prices. Likewise, Past Hour and Past Day mean the use of ODAX data of previous hour and past day in the estimation of implied volatilities of the ODAX. MINSPAN and REPLACE ALL procedures are adapted from Harris et al. (1995) and detail explanations are contained in text. Note that using past 15 mintues data to estimate implied volatility of the ODAX will always yield the highest number of observations. It is because only the first 15 minutes data of the dataset is lost due to estimation, while an hour and a day's data are lost if data of past hour and past day are used.

where Y_t is a (3 X 1) vector containing the current returns of the DAX securities; X_t is an (3p X 1) vector containing p lags of returns of the DAX securities; C is the vector of constant (intercepts); matrix A contains the autoregressive coefficients and ϵ_t is the vector of random errors.[10]

The Granger-causality tests should also take into account of possible heteroscedasticity, autocorrelation and possible contempaneous correlations of the error terms. This dissertation uses the Generalized Method of Moments (GMM) estimates in performing the Granger causality tests. The GMM procedure imposes very weak distributional assumptions and can account for the presence of conditional heteroscedasticity of an unknown form (Greene (1993)). Since the Q-test and the LM test results in Chapter 2 show that returns of the DAX securities exhibit ARCH effects, GMM is also an appropriate estimation method here.

3.4.2 Cointegration

Two or more time series are said to be cointegrated if they are integrated series of the same order and a linear combination of them is I(0). Checking whether the DAX securities are cointegrated is necessary because of two reasons. First, if the DAX securities are cointegrated, the VAR model discussed earlier is misspecified. Granger (1969) first put forward the causality tests and historically, researchers use error correction terms in Granger causality tests without theoretical justifications. According

[10] If the system is cointegrated (to be discussed in next sub-section), then an error correction term should be added.

to the Granger Representation Theorem (Engle and Granger, 1987) , an error correction term should be included in the cointegrated system.

Second, the Gonzalo and Granger (1995) information sharing model requires the series under study to be cointegrated. Therefore, it is necessary to examine whether the three DAX securities are cointegrated or not before applying the information sharing model. This step is important, since the information model chosen, hence validity of empirical results, will depend on whether the prices of the three DAX securities are cointegrated.

In determining the possible cointegration relationships, the first step is to examine whether the price series of the DAX securities contain unit roots. As pointed out earlier, cointegration requires the series to be integrated processes of the same order. Augmented Dickey-Fuller (ADF) and Philips-Perron (PP) tests are used to test for the existence of unit roots. PP test is also used because of the existence of possible heteroscedasticity and serial correlation. The second step is to test for cointegration among the DAX securities if the variables are I(1) series. The ADF test is used to test bivariate cointegration relationships between the DAX securities while the multivariate *trace* test and λ_{max} test developed in Johansen (1988, 1991) are used in the multivariate case.

To perform the ADF and PP tests on stationarity of the DAX securities, the following regressions are run:

$$R_t = \alpha + \beta \ln P_{t-1} + \sum_{i=1}^{m} \gamma_i R_{t-i} + \phi t + e_t , \tag{3.10}$$

$$\Delta R_t = \alpha + \beta R_{t-1} + \sum_{i=1}^{m} \gamma_i \Delta R_{t-i} + \phi t + e_t \,, \tag{3.11}$$

where $R_t = \ln(P_t / P_{t-1})$, t is the time trend, α, β, ϕ and γ_i are parameters to be estimated and m is the number of lags.[11] If the β coefficient from equation (3.10) is not significantly different from zero and that of the equation (3.11) is significantly different from zero, then the series is an I(1) process. The ADF test statistic is the same as the t-statistic in (3.11), though the critical values are different. Critical values are obtained from Hamilton (1994).

The PP test statistic, ρ, is defined as:

$$\rho = T(\hat{\beta} - 1) - \frac{1}{2}(T^2 \cdot \hat{\sigma}_\beta / s^2) \cdot (\hat{\psi}^2 - \hat{\omega}_0) \,, \tag{3.12}$$

where T is the number of observations, $\hat{\sigma}^2_\beta$ is the standard error of β, s^2 is the variance of the residuals, e_t, $\hat{\omega}_j$ is the autocovariance of the residuals, q is the number of lags and $\hat{\psi}^2$ is defined as:

$$\hat{\psi}^2 = \hat{\omega}_0 + 2 \cdot \sum_{j=1}^{q} [1 - j/(q+1)] \, \hat{\omega}_j \,. \tag{3.13}$$

To test for pairwise cointegration relationships among the DAX, the FDAX and the implied values of ODAX, the IDAX, the following cointegrating regression is run:

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[11] Following Schwert (1987), the number of lags used is $m = \mathrm{INT}\{12*(T/100)^{1/4}\}$, where INT is the integer function, T is the number of observations. For the MINSPAN and REPLACE ALL procedures, 61 lags are used. At a first glance, it is hard to justify economically why so many lags are used. However, increasing the number of lags will decrease the probability of finding stationary. Thus, the results are shown to be robust across the choice of lags in regression models.

$$\ln(P_{k,t}) = \alpha_1 + \beta\ln(P_{j,t}) + \phi t + V_t , \tag{3.14}$$

where P_j and P_k = values of the DAX, the FDAX and the IDAX at time t with j $\neq$ k, t is the time trend, and V_t is the residual. The residuals are then tested for unit roots. If the residuals of equation (3.14) are stationary, i.e., an I(0) process, then the two series are cointegrated. To test for the stationarity of V_t in (3.14), the following regression is run:

$$\Delta V_t = \beta V_{t-1} + \sum_{i=1}^{m}\gamma_i \Delta V_{t-i} + u_t . \tag{3.15}$$

If β is significantly negative, then the two series are cointegrated.

Under a multivariate framework, the cointegrated system can be specified in form of a vector error correction model (VECM):

$$\Delta X_t = \mu + \sum_{j=1}^{k-1}\Gamma_j \Delta X_{t-j} + \Pi X_{t-1} + \epsilon_t , \tag{3.16}$$

where Δ is the first difference operator, X_t is the vector of natural logarithms of prices of the DAX securities, Γ_js are 3 X 3 parameter matrices, and Π is the cointegrating matrix, ϵ_t is the Gaussian white noise process. Since there is cointegration, matrix Π is less than full rank. Johansen (1988, 1991) develops a procedure of using maximum likelihood method to construct the λ_{max} and *trace* test statistics for testing for the existence of cointegration within a system of equations. The *trace* test statistic is calculated as:

$$TR = -T\sum_{i=r+1}^{k-1} \ln(1 - \hat{\lambda}_i) , \tag{3.17}$$

and the λ_{max} test statistic is:

$$\lambda_{max} = -T \ln(1 - \hat{\lambda}_{r+1}) , \tag{3.18}$$

where T is the number of observations, λ_is are the eigen values of Π in (3.16). Detailed proof and formulae of the Johansen test statistics are not given here and the reader is referred to Johansen (1988, 1991). Critical values of the Johansen cointegration tests are obtained from Johansen and Juselius (1990) and Osterwald-Lenum (1992).

3.4.3 Information Sharing

The idea of information sharing comes from the common stochastic trends (the common factor) that shared by cointegrated time series. Four models that estimate the common factor in the cointegrated system can be used: a reduced form vector moving average (VMA) model, the King et al. (1991) model, the Hasbrouck (1995) model, and the Gonzalo and Granger (1995) model.

Tse (1996) compares the robustness of these four different models in price discovery of IBM in the NYSE, the PSE and the MWSE. He finds that the Hasbrouck (1995) model is over-identified and imposes inaccurate restrictions. One restriction is that the Hasbrouck model cannot be used in systems with more than one common factor. The degree of information sharing under the Hasbrouck model is also affected by correlation across markets. If the markets are contemporaneously correlated, ambiguous

results are obtained. As shown in Tse (1996), informationally linked securities are contemporaneously correlated; and empirically the Hasbrouck model is incapable in estimating the common stochastic trends (the common factors, hence information sharing) among the economic series. In addition, the sequence of entering variables will affect the degree of information sharing. The first variable in the system will always have the largest information share. Thus, ambiguous results / conclusions will be drawn based on the Hasbrouck model. Furthermore, there are no formal tests on the significance of individual series in the degree of information sharing in the Hasbrouck model. On the other hand, the VMA, King et al. (1991) and Gonzalo and Granger (1995) models provide unambiguous results in the price discovery process.

One drawback of the VMA approach, however, is that it does not identify the common factor. It only shows whether one series is affected by the stochastic components of other series. Under the King et al. (1991) approach, the variance decomposition (VDC) and cumulative impulse response function (CIRF) attributed by each common trend can be estimated. The response of the securities to innovations (information sharing) in the common factor can then be examined. One drawback of the King et al. (1991) model is that there is no explicit testing on the importance of a particular security in the common factor is made. On the other hand, the Gonzalo and Granger (1995) model can estimate the common factor even there is correlation across market innovations. In addition, the Gonzalo and Granger model is also compatible with the King et al. (1991) model and is robust to non-normal innovations. Most important, there is formal testing on the importance of a particular security in the common factor.

Based on the above discussion, the Gonzalo and Granger (1995) (GG) model of information sharing is used. The GG model is chosen because it can provide unambiguous results when the markets under study are contemporaneously correlated (Tse (1996)). Furthermore, the GG model can explicitly test the relative importance of individual series as the sole component of the common factor. In this way, the relative importance and significance of the securities in the common factor can be examined.

3.4.4 The Gonzalo and Granger (1995) Information Sharing Model

Recall that a cointegrated system can be described in equation (3.16). The matrix Π can further be decomposed into $\alpha\beta'$, where β is the matrix of cointegrating vectors. Suppose there are p variables and r cointegrating vectors in (3.16). Let f_t be the common factors of the system. The elements of X_t can be explained in terms of (p-r) I(1) variables, the common factors f_t, and some I(0) components Y_t. That is,

$$X_t = A_1 f_t + Y_t \; . \tag{3.19}$$

For example, for a three variable system (p = 3) with two cointegrating vectors (r = 2), there will be one common factor (m = p - r). GG further impose the identification to be $f_t = \gamma X_t$, where γ is a m x p coefficient matrix of the common factor matrix f_t. This condition not only helps to identify f_t, but it also helps to relate f_t with the observed variables. Multiplying (3.16) by γ, (3.16) becomes:

$$\Delta f_t = \gamma\mu + \gamma\alpha\beta' X_{t-1} + \gamma\sum_{i=1}^{k-1}\Gamma_i \Delta X_{t-i} + \gamma\epsilon_t \; .$$

For X_t to have no long run impact on f_t, (3.19) implies that:

$$f_t = \alpha_{\perp}^{*\prime} X_t \,. \tag{3.21}$$

Based on Johansen (1991), GG develop the maximum likelihood estimator of γ. For a restriction matrix G such that the null hypothesis is $G\theta = \gamma$, the likelihood ratio test statistic Q^* is:

$$Q^* = -T \sum_{r+1}^{p} \ln[(1 - \hat{\lambda}^*_{i+m-p}) \,/\, (1 - \hat{\lambda}_i)] \,, \tag{3.22}$$

where λ^* is the largest eigen value from the model under the null and is distributed as a χ^2 variate with degree of freedom (p-r) x m. The restriction matrix G can be chosen such that it restricts the null to be X_i as the only component in the common factor. When there is only one common factor (i.e., m = 1 and p - r = 1), and under the null X_i is the sole element in the common factor, Q^* is distributed as a $\chi^2(1)$ variate.

3.5 Hypotheses

3.5.1 Hypothesis One

The first hypothesis to be tested is whether returns of the derivatives lead the returns of the cash market. FOW use the Sims approach of causality to investigate whether futures lead options, and options lead the spot. As discussed above, the Sims approach to causality is only statistically appealing and has little economic intuition. In addition, the role of the cash index in the causal relationship is ignored in FOW. To shed light on which derivative is more efficient in processing information, pair-wise

Granger-causality tests are run between the DAX securities. The first hypothesis is to test whether futures lead options, futures leads spot and options lead the spot. If derivatives are more efficient in processing information, derivatives are expected to lead the spot market. Furthermore, which derivative is more efficient can also be tested through a Granger causality test between the FDAX and the ODAX. The first hypothesis to be tested is:

H_{10}: *Index futures do not lead the index option.*

H_{11}: *Index futures lead the index option.*

H_{20}: *Index futures do not lead the spot index.*

H_{21}: *Index futures lead the spot index.*

H_{30}: *Index options do not lead the spot index.*

H_{31}: *Index options lead the spot index.*

3.5.2 Hypothesis Two

Hypothesis one only tests whether the derivatives lead the stock index on a one-by-one basis. Like previous works, hypothesis one only examines the lead-lag relationships among the index securities within a bivariate framework. However, the results may be biased if the dominant derivative is excluded in the bivariate analysis. For example, if index futures are the dominant securities in the pricing function, the lead-lag relationship between index options and the cash index may be a manifestation of the lead-lag relationships between the two derivatives, and futures and spot indexes. The second hypothesis studies the lead-lag relationship under a multivariate Granger-

causality framework, with all the three DAX securities considered together as a whole system. The second hypothesis to be tested is:

H_0: *Derivatives do not lead the stock index.*

H_1: *Derivatives lead the stock index.*

3.5.3 Hypothesis Three

The first two hypotheses only examine the lead-lag relationships of the returns of the DAX securities. To certain extent, these two hypotheses are confirmations of previous work by incorporating new data and by different approaches in handling the data. Apart from studying the lead-lag relationships, this dissertation also examines the degree of information sharing among the index securities. As discussed above, a first step of testing whether there is cointegration among the prices of the DAX securities has to been done. This step is necessary since the appropriate information sharing models will depend on whether there is cointegration among the DAX securities. The third hypothesis to be tested is:

H_0: *Derivatives and the spot index have the same share of information.*

H_1: *Derivatives and the spot index do not have the share of information.*

3.6 Empirical Results and Discussions

3.6.1 Testing for Unit Roots

The natural logarithms of the DAX, the FDAX and implied DAX from the ODAX prices are tested for stationarity. Table 3.4 presents the results for unit root tests for the DAX securities. Both the ADF and PP tests, with or without a time trend included, are used. For the level series, all the three series are not stationary, as

Table 3.4

Test of Stationarity of the DAX Securities

	Panel A: MINSPAN Procedure with Call ODAX			
	Without Trend		With Trend	
Securities	Level	First Difference	Level	First Difference
DAX	-0.558	-27.218***	-1.590	-27.224***
	(-1.215)	(-621.83)***	(-1.804)	(-571.30)***
FDAX	-0.601	-27.420***	-1.685	-27.426***
	(-1.217)	(-621.43)***	(-1.803)	(-571.88)***
ODAX1	-0.566	-28.341***	-1.566	-28.346***
	(-1.214)	(-622.61)***	(-1.801)	(-569.78)***
ODAX2	-0.534	-29.400***	-1.538	-29.406***
	(-1.214)	(-628.04)***	(-1.802)	(-557.30)***
ODAX3	-0.520	-28.072***	-1.521	-28.078***
	(-1.214)	(-606.68)***	(-1.802)	(-586.14)***

	Panel B: MINSPAN Procedure with Put ODAX			
	Without Trend		With Trend	
Securities	Level	First Difference	Level	First Difference
DAX	-0.460	-27.922***	-1.536	-27.930***
	(-1.223)	(-623.84)***	(-1.799)	(-573.64)***
FDAX	-0.494	-28.450***	-1.617	-28.459***
	(-1.225)	(-626.05)***	(-1.798)	(-569.56)***
ODAX4	-0.463	-29.702***	-1.524	-29.709***
	(-1.222)	(-620.58)***	(-1.799)	(-578.46)***
ODAX5	-0.488	-30.903***	-1.539	-30.910***
	(-1.222)	(-623.25)***	(-1.800)	(-575.59)***
ODAX6	-0.632	-29.738***	-1.691	-29.744***
	(-1.221)	(-632.01)***	(-1.800)	(-540.54)***

(table cont'd.)

Panel C: REPLACE ALL Procedure with Call ODAX				
	Without Trend		With Trend	
Securities	Level	First Difference	Level	First Difference
DAX	-0.552	-27.769***	-1.583	-27.775***
	(-1.173)	(-634.77)***	(-1.845)	(-576.54)***
FDAX	-0.597	-28.031***	-1.682	-28.038***
	(-1.175)	(-634.28)***	(-1.845)	(-577.42)***
ODAX1	-0.569	-28.540***	-1.566	-28.545***
	(-1.172)	(-622.94)***	(-1.846)	(-592.86)***
ODAX2	-0.534	-29.740***	-1.535	-29.745***
	(-1.172)	(-638.49)***	(-1.844)	(-567.97)***
ODAX3	-0.518	-28.513***	-1.502	-28.518***
	(-1.172)	(-638.82)***	(-1.844)	(-560.84)***

Panel D: REPLACE ALL Procedure with Put ODAX				
	Without Trend		With Trend	
Securities	Level	First Difference	Level	First Difference
DAX	-0.458	-28.574***	-1.532	-28.582***
	(-1.181)	(-635.00)***	(-1.841)	(-580.37)***
FDAX	-0.485	-29.193***	-1.610	-29.203***
	(-1.182)	(-634.27)***	(-1.840)	(-581.48)***
ODAX4	-0.434	-30.708***	-1.501	-30.716***
	(-1.181)	(-644.82)***	(-1.841)	(-550.52)***
ODAX5	-0.452	-31.757***	-1.509	-31.764***
	(-1.180)	(-631.51)***	(-1.841)	(-587.01)***
ODAX6	-0.610	-30.436***	-1.656	-30.441***
	(-1.179)	(-637.40)***	(-1.842)	(-572.47)***

*** Significant at 0.1%.

Level refers to the log transformation of the original series while First Difference refers to the first difference of the Level series. Tests for stationarity are done by both the Augmented Dicky-Fuller (ADF) and the Phillips-Perron (PP) tests. Number with no parentheses are the ADF test statistics while numbers in parentheses are the PP test statistics.

evidenced by the insignificant ADF and PP test statistics. This finding is robust across the choice of put and call options and the use of different measures of implied volatilities in the calculation of the implied DAX. For the first difference series, both the ADF and PP test statistics are highly significant, suggesting that the returns of the DAX securities are stationary. Again, this finding is not affected by the choice of asset types or measures of implied volatilies, and with or without time trend included in the cointegrating regression. This observation suggests that the prices of the DAX securities follow I(1) processes. The large and significant PP test statistics mean that this finding is also robust in the presence of heteroscedasticity. The existence of unit roots in the prices of the DAX securities leads to the question of whether the DAX securities are cointegrated.

3.6.2 Testing for Cointegration

Table 3.5 presents the results for bivariate cointegration relationships among the DAX securities under different data collection procedures and estimates of implied volatilities. The ADF test is used to test for the existence of bivariate cointegration relationships. From Table 3.5, all ADF test statistics for testing cointegration between DAX and ODAX are significant at 0.1%. This shows that there is cointegration between the DAX and the ODAX and the results are robust across different data collection procedures. That means, there exists a long run equilibrium relationship between the DAX and the ODAX. One interesting point is that, the test statistics are more significant (the test statistics are larger in magnitudes) for the DAX and put ODAX pair than the DAX and the call ODAX pair. This finding, together with the differences in intraday

Table 3.5

Results of Bivariate Cointegration Results

Data Collection Procedure	Variables	Without Trend	With Trend
MINSPAN	DAX and FDAX	-0.952	-0.939
	DAX and ODAX1	-15.920***	-15.963***
	FDAX and ODAX1	-1.484	-1.480
MINSPAN	DAX and FDAX	-0.957	-0.947
	DAX and ODAX2	-18.486***	-18.479***
	FDAX and ODAX2	-3.095	-2.937
MINSPAN	DAX and FDAX	-1.003	-0.982
	DAX and ODAX3	-6.667***	-6.662***
	FDAX and ODAX3	-1.299	-0.811
REPLACE ALL	DAX and FDAX	-0.916	-0.940
	DAX and ODAX1	-16.410***	-16.486***
	FDAX and ODAX1	-1.525	-1.598
REPLACE ALL	DAX and FDAX	-0.917	-0.941
	DAX and ODAX2	-19.601***	-19.597***
	FDAX and ODAX2	-3.449	-3.250
REPLACE ALL	DAX and FDAX	-0.984	-0.989
	DAX and ODAX3	-6.854***	-6.850***
	FDAX and ODAX3	-1.242	-0.812
MINSPAN	DAX and FDAX	-2.230	-2.569
	DAX and ODAX4	-30.862***	-30.667***
	FDAX and ODAX4	-2.010	-2.231
MINSPAN	DAX and FDAX	-2.202	-2.539
	DAX and ODAX5	-31.634***	-31.557***
	FDAX and ODAX5	-3.211	-3.242
MINSPAN	DAX and FDAX	-2.326	-2.627
	DAX and ODAX6	-7.644***	-7.664***
	FDAX and ODAX6	-2.095	-2.197
REPLACE ALL	DAX and FDAX	-2.364	-2.707
	DAX and ODAX4	-29.689***	-29.592***
	FDAX and ODAX4	-2.742	-2.788

(table cont'd.)

REPLACE ALL	DAX and FDAX	-2.340	-2.685
	DAX and ODAX5	-32.001***	-31.920***
	FDAX and ODAX5	-3.508	-3.397
REPLACE ALL	DAX and FDAX	-2.456	-2.766
	DAX and ODAX6	-7.876***	-7.894***
	FDAX and ODAX6	-2.240	-2.349

*** Significant at 0.1%.

The test statistics are those of the Augmented Dicky-Fuller (ADF) test statistics of bivariate cointegration. See text for details of data collection procedures.

return behaviors of puts and calls (see Chapter 2), suggests that the puts and calls play different roles in the price discovery process.

Apart from finding cointegration between the DAX and the ODAX, no cointegration relationship exists between other DAX securities. Finding no cointegration between the DAX and the FDAX is counter intuitive. However, as put forward in BBL, the special feature of having dividends reinvested in the calculation of the DAX will lead to the dominance of interest rates in the cointegrating regression. As the interest rate is I(1), the I(1) component will be transmitted to the residuals of the cointegrating regression, making the DAX not cointegrated with the FDAX.[12] This finding of no cointegration between the DAX and the FDAX is consistent with the empirical results in BBL. The input here is that the ODAX is not cointegrated with the FDAX either.[13]

The above cointegrating results are only valid under the bivariate framework. As mentioned earlier in this chapter, one void in previous studies is that only two securities are considered at one time. To test for the cointegration relationships among the three securities, the Johansen tests are used. Results of the Johansen tests (both the *trace* test statistics and the λ_{max} test statistics) are given in Table 3.6. The null hypothesis of no cointegration is rejected overwhelmingly by the large *trace* and λ_{max} test statistics. Under the significance level of 0.1%, empirical results show that the three securities are cointegrated with two cointegrating vectors. Thus, there exists a long run equilibrium

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[12] The findings in BBL suggest that the cointegration model is poorly specified. However, it cannot be remedied because of the lack of intraday data on interest rates.

[13] Note that the calculation of the implied DAX has already taken away the effects of interest rates.

Table 3.6

Results of Johansen Cointegration Tests

Data Collection Procedures	H_0:	λ_{max}	*trace*	Eigen Value
MINSPAN with ODAX1	$r \leq 0$	1550.24***	1603.03***	0.0338
	$r \leq 1$	52.52***	52.79***	0.0012
	$r \leq 2$	0.27	0.27	0.0000
MINSPAN with ODAX2	$r \leq 0$	990.48***	1041.12***	0.0218
	$r \leq 1$	50.36***	50.64***	0.0011
	$r \leq 2$	0.28	0.28	0.0000
MINSPAN with ODAX3	$r \leq 0$	460.10***	512.53***	0.0102
	$r \leq 1$	52.19***	52.43***	0.0012
	$r \leq 2$	0.24	0.24	0.0000
MINSPAN with ODAX4	$r \leq 0$	1861.88***	1917.45***	0.0403
	$r \leq 1$	55.36***	55.57***	0.0012
	$r \leq 2$	0.21	0.21	0.0000
MINSPAN with ODAX5	$r \leq 0$	1102.04***	1157.37***	0.0240
	$r \leq 1$	55.12***	55.33***	0.0012
	$r \leq 2$	0.21	0.21	0.0000
MINSPAN with ODAX6	$r \leq 0$	497.61***	544.71***	0.0110
	$r \leq 1$	46.87***	47.10***	0.0010
	$r \leq 2$	0.21	0.21	0.0000
REPLACE ALL with ODAX1	$r \leq 0$	1616.86***	1670.38***	0.0341
	$r \leq 1$	53.25***	53.52***	0.0011
	$r \leq 2$	0.27	0.27	0.0000
REPLACE ALL with ODAX2	$r \leq 0$	987.39***	1038.57***	0.0210
	$r \leq 1$	50.91***	51.18***	0.0011
	$r \leq 2$	0.27	0.27	0.0000

(table cont'd.)

REPLACE ALL with ODAX3	$r \leq 0$	439.41***	488.92***	0.0094
	$r \leq 1$	49.28***	49.51***	0.0011
	$r \leq 2$	0.24	0.24	0.0000
REPLACE ALL with ODAX4	$r \leq 0$	1632.44***	1688.60***	0.0342
	$r \leq 1$	55.95***	56.16***	0.0012
	$r \leq 2$	0.21	0.21	0.0000
REPLACE ALL with ODAX5	$r \leq 0$	1102.09***	1157.98***	0.0232
	$r \leq 1$	55.67***	55.88***	0.0012
	$r \leq 2$	0.21	0.21	0.0000
REPLACE ALL with ODAX6	$r \leq 0$	499.37***	547.24***	0.0106
	$r \leq 1$	47.65***	47.87***	0.0010
	$r \leq 2$	0.22	0.22	0.0000

*** Significant at 0.1%.

λ_{max} is the Johansen maximum Lambda test statistic, *trace* is the Johansen's *trace* test statistic. H_0 is the null hypotheses that the system contains at most r cointegrating vectors. The number of lags are those used in the vector autoregressive (VAR) model, which is determined by the SIC. See notes of Table 3.4 and text for details of various data collection procedures.

relationship among the index securities. Existence of two cointegrating vectors also shows that the DAX securities are affected by one common stochastic factor.

From a theoretical point of view, there is strong justification to apply information sharing models since there is cointegration in the whole system, though DAX and the FDAX, the FDAX and the ODAX are not cointegrated. Therefore, the Gonzalo and Granger information sharing model can be used to extract the relative importance of the DAX, the FDAX and the ODAX in the price discovery process. Before discussing the results of information sharing, a first look at the causality relationship is presented in the next section.

3.6.3 Bivariate Granger Causality

Since the DAX and the ODAX are cointegrated, the VAR model in (3.9) is misspecified. The VAR system must include an error correction term (EC). The EC term measures the adjustment of the dependent variable to the disparity between the independent and dependent variables in a previous period. However, for the bivariate relationships that involve the FDAX, no EC term is needed since the FDAX is not cointegrated with either the DAX or the ODAX. The following models are used:

$$\Delta DAX_t = \alpha + \beta\, \Delta DAX_{t-1} + \gamma\, \Delta FDAX_{t-1} + \epsilon_t, \tag{3.23a}$$

$$\Delta DAX_t = \alpha + \beta\, \Delta DAX_{t-1} + \gamma\, \Delta ODAX_{t-1} + \mu\, (DAX_{t-1} - ODAX_{t-1}) + \epsilon_t, \tag{3.23b}$$

$$\Delta FDAX_t = \alpha + \beta\, \Delta DAX_{t-1} + \gamma\, \Delta FDAX_{t-1} + \epsilon_t, \tag{3.23c}$$

$$\Delta FDAX_t = \alpha + \beta\, \Delta FDAX_{t-1} + \gamma\, \Delta ODAX_{t-1} + \epsilon_t \tag{3.23d}$$

$$\Delta ODAX_t = \alpha + \beta\, \Delta DAX_{t-1} + \gamma\, \Delta ODAX_{t-1} + \mu\, (ODAX_{t-1} - DAX_{t-1}) + \epsilon_t, \tag{3.23e}$$

$$\Delta ODAX_t = \alpha + \beta\, \Delta FDAX_{t-1} + \gamma\, \Delta ODAX_{t-1} + \epsilon_t. \tag{3.23f}$$

Note that only one lag is used in the above models. It is because lag one will mean information contained in the last trade and such information is most recent. As Granger causality depicted in (3.8) requires past values of the independent variables to be informative in forecasting the dependent variables, one lag is also appropriate. Furthermore, the time intervals between lags in using the REPLACE ALL or MINSPAN approaches are not fixed. Unlike using minute by minute data, in which one lag will mean one minute, lags in the MINSPAN or REPLACE ALL procedures do not have specific meanings in terms of time.

Results of the bivariate Granger causality tests are presented in Table 3.7. Parameters estimated under the MINSPAN and REPLACE ALL procedures are very similar and empirical results are qualitatively the same. Discussion here is then based on results of the REPLACE ALL procedure. Panel B of Table 3.7 gives the results for the REPLACE ALL procedure. There is strong evidence that the DAX and the FDAX Granger-cause each other, as shown by the fact that the parameters γ in (3.23a) and β in (3.23c) are highly significant. Note that the magnitudes of the two parameters are very similar, a rough guess would suggest that the previous lag of both securities are about equally important in the lead-lag relationship.[14] Another point to note is that the R^2 of model (3.23a) (0.0050) is higher than that of model (3.23c) (0.0016). This means that the FDAX has better forecasting ability in future DAX returns than the vice versa.

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[14] BBL show that the significance of lags of DAX dies out very quickly (about two to three lags) while lags of FDAX remains significant up to 20 lags for model. The reader is referred to BBL for a detailed study on the minute-by-minute lead-lag relationship between the DAX and the FDAX.

Table 3.7

Results of Bivariate Granger Causality Tests

Panel A: MINSPAN Procedure					
Hypothesis	α	β	γ	μ	R^2
FDAX does not GC DAX	0.000006	0.0082	0.0538***	NA	0.0051
ODAX1 does not GC DAX	0.000009	0.0696***	-0.0105***	-0.0202***	0.0047
DAX does not GC FDAX	0.000006	0.0716***	-0.0592***	NA	0.0014
ODAX1 does not GC FDAX	0.000006	-0.0140*	0.0028	NA	0.0002
DAX does not GC ODAX1	-0.00007***	0.1970***	-0.1719***	-0.5031***	0.2674
FDAX does not GC ODAX1	0.000007	0.3634***	-0.4225***	NA	0.1517
ODAX2 does not GC DAX	0.000009	0.0660***	-0.0070*	-0.0179***	0.0050
ODAX2 does not GC FDAX	0.000006	-0.0154**	0.0047	NA	0.0002
DAX does not GC ODAX2	-0.00003***	0.3258***	-0.3099***	-0.2716***	0.2231
FDAX does not GC ODAX2	0.000007	0.3807***	-0.4463***	NA	0.1670
ODAX3 does not GC DAX	0.000007	0.0658***	-0.0059	-0.0138***	0.0049
ODAX3 does not GC FDAX	0.000006	-0.0140*	0.0027	NA	0.0002
DAX does not GC ODAX3	-0.000006	0.3485***	-0.3591***	-0.1641***	0.1991
FDAX does not GC ODAX3	0.000007	0.3621***	-0.4425***	NA	0.1655
ODAX4 does not GC DAX	0.000008	0.0650***	-0.0029	-0.0080***	0.0044
ODAX4 does not GC FDAX	0.000006	-0.0130*	0.0019	NA	0.0002
DAX does not GC ODAX4	-0.000167***	0.1511***	-0.0997***	-0.6994***	0.3741
FDAX does not GC ODAX4	0.000007	0.4038***	-0.4497***	NA	0.1940
ODAX5 does not GC DAX	0.000007	0.0635***	-0.0011	-0.0061***	0.0043
ODAX5 does not GC FDAX	0.000006	-0.0136**	0.0028	NA	0.0002
DAX does not GC ODAX5	-0.000119***	0.2467***	-0.1867***	-0.5626***	0.3482
FDAX does not GC ODAX5	0.000007	0.4212***	-0.4676***	NA	0.2090
ODAX6 does not GC DAX	0.000009	0.0645***	-0.0021	-0.0062***	0.0044
ODAX6 does not GC FDAX	0.000006	-0.0135*	0.0026	NA	0.0002
DAX does not GC ODAX6	-0.000167	0.3764***	-0.2738***	-0.3992***	0.3079
FDAX does not GC ODAX6	0.000006	0.4536***	-0.4729***	NA	0.2118

(table cont'd.)

Panel B: REPLACE ALL Procedure					
Hypothesis	α	β	γ	μ	R^2
FDAX does not GC DAX	0.000006	0.0120	0.0503***	NA	0.0050
ODAX1 does not GC DAX	0.000009	0.0695***	-0.0099***	-0.0210***	0.0049
DAX does not GC FDAX	0.000006	0.0747***	-0.0643***	NA	0.0016
ODAX1 does not GC FDAX	0.000006	-0.0193***	0.0051	NA	0.0003
DAX does not GC ODAX1	-0.000069***	0.2016***	-0.1764***	-0.4967***	0.2678
FDAX does not GC ODAX1	0.000007	0.3584***	-0.4235***	NA	0.1533
ODAX2 does not GC DAX	0.000008	0.0653***	-0.0059	-0.0183***	0.0052
ODAX2 does not GC FDAX	0.000006	-0.0210***	0.0073*	NA	0.0004
DAX does not GC ODAX2	-0.000030***	0.3217***	-0.3076***	-0.2693***	0.2216
FDAX does not GC ODAX2	0.000007	0.3717***	-0.4424***	NA	0.1654
ODAX3 does not GC DAX	0.000007	0.0651***	-0.0048	-0.0139***	0.0050
ODAX3 does not GC FDAX	0.000006	-0.0194***	0.0053	NA	0.0003
DAX does not GC ODAX3	-0.000007	0.3461***	-0.3573***	-0.1636***	0.1989
FDAX does not GC ODAX3	0.000007	0.3580***	-0.4404***	NA	0.1653
ODAX4 does not GC DAX	0.000008	0.0652***	-0.0022	-0.0076***	0.0045
ODAX4 does not GC FDAX	0.000006	-0.0130*	0.0015	NA	0.0002
DAX does not GC ODAX4	-0.000166***	0.1668***	-0.1117***	-0.6758***	0.3686
FDAX does not GC ODAX4	0.000007	0.4029***	-0.4500***	NA	0.1944
ODAX5 does not GC DAX	0.000007	0.0639***	-0.0008	-0.0061***	0.0044
ODAX5 does not GC FDAX	0.000006	-0.0135**	0.0021	NA	0.0002
DAX does not GC ODAX5	-0.000121***	0.2499***	-0.1848***	-0.5606***	0.3467
FDAX does not GC ODAX5	0.000007	0.4193***	-0.4649***	NA	0.2069
ODAX6 does not GC DAX	0.000008	0.0659***	-0.0025	-0.0061***	0.0046
ODAX6 does not GC FDAX	0.000006	-0.0134*	0.0020	NA	0.0002
DAX does not GC ODAX6	-0.000166***	0.3775***	-0.2715***	-0.3973***	0.3058
FDAX does not GC ODAX6	0.000006	0.4486***	-0.4695***	NA	0.2090

(table cont'd.)

Panel C: Half Lives of Error Correction Terms					
		MINSPAN		REPLACE ALL	
Dependent Variable	Independent Variable	Value of ECTerm	Half Life	Value of EC Term	Half Life
DAX	ODAX1	-0.0202	34.97	-0.0210	32.66
DAX	ODAX2	-0.0179	38.38	-0.0183	38.53
DAX	ODAX3	-0.0138	49.88	-0.0139	49.50
DAX	ODAX4	-0.0080	86.30	-0.0076	90.86
DAX	ODAX5	-0.0061	113.28	-0.0061	113.28
DAX	ODAX6	-0.0062	111.45	-0.0061	113.28
ODAX1	DAX	-0.5031	0.99	-0.4967	1.01
ODAX2	DAX	-0.2716	2.21	-0.2693	2.24
ODAX3	DAX	-0.1641	3.88	-0.1636	3.89
ODAX4	DAX	-0.6994	0.71	-0.6758	0.74
ODAX5	DAX	-0.5626	0.89	-0.5606	0.89
ODAX6	DAX	-0.3992	1.42	-0.3973	1.43

* Significant at 1%, ** Significant at 0.5%, *** Significant at 0.1%

However, both R^2 are still small in magnitudes that do not provide much economic significance.

For the case between the FDAX and the ODAX, the results become more drastic. For example, ODAX does not Granger-cause the FDAX but the FDAX Granger-causes ODAX. Note that the R^2 of model (3.23f) is 0.1533, which is much higher than that of 0.0003 in model (3.23d). The large R^2 in model (3.23f) suggests that the FDAX is useful in the forecasting of future returns of the ODAX. This result also holds for other measures of ODAX returns, which means that the above observation is robust across the choice of put and call options and under different estimates of implied volatilities. In addition, parameter β in model (3.23f) is also large in magnitude. This means that the above result is not just statistically significant, but also economically significant. An one percent increase in return of FDAX in a previous period will lead to 0.36% increase in the ODAX return. To conclude, under a bivariate case, the FDAX dominates the ODAX in the price discovery process.

The next case to be considered in the lead-lag relationship is between the DAX and the ODAX. Since the two securities are cointegrated, an error correction term is needed. The error correction terms can also capture the effects of adjustments to price disparity between the DAX and the ODAX. Consider models (3.23b) and model (3.23e). Three important observations are made here. First, results from these two models show that there is a bidirectional Granger causality relationship between the DAX and the ODAX, as both the parameters γ in model (3.23b) and β in model (3.23e) are highly significant. However, β is much larger than γ in terms of magnitude, after normalized

by their standard errors. The "normalized" β value is 17.96356, while the "normalized" value of γ is only -4.02616. This shows that the DAX influences the ODAX much more than that of the ODAX influences the DAX. Second, the error correction terms are significant under both models. This suggests that disparity between the DAX and the ODAX provides new information to the pricing relationship. Third, though the error correction terms μ in both models are highly significant, μ in model (3.23e) is much higher than that in model (3.23b). To examine the time it takes for a market to return to equilibrium after a shock, the measure of half life (HL) is used. HL is the time it takes for a shock to "decay" (a concept similar to the decay of weight of radioactive chemical elements) its impact by one half.[15] An analysis of HL is shown in Panel C of Table 3.7. For a shock in the DAX, the reaction of the ODAX is immediate. The range of HL is between 0.74 and 3.89, which means, it takes at most 3.89 periods for the ODAX to adjust the shock of the DAX by one half. This shows that ODAX reacts quickly to the disparity between the DAX and the ODAX in a previous period. On the other hand, the reaction of the DAX is much slower. The HL is between 32.66 and 113.28 periods, which suggests that the DAX adjusts slowly to shocks in the ODAX. Fourth, the R^2 of model (3.23e) is 0.2674, which is much higher than that of 0.0047 in model (3.23b). The larger R^2 in model (3.23e) means that the DAX plays a significant role (both economical and statistical) in the forecasting of future returns of the ODAX. However, the role of ODAX in forecasting returns of the DAX is not that prominent.

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[15] As shown in Booth et al. (1996), HL is inversely related to μ. HL is well defined for $1 \geq |\mu| > 0$. When $\mu=0$ or $\mu>1$, HL is ill-defined.

Again, the above analysis is also robust across the choices of types of options and estimates of implied volatilies. Overall results suggest that the DAX be the primary driving force in the bivariate causality relationship between the DAX and the ODAX. From an information processing perspective, ODAX reacts and adjusts *rapidly* to new information in the DAX but the DAX adjusts *slowly* to new information in the ODAX.

The above discussion can best be summarized graphically in Figure (3.1). The arrows in this figure denote causal relationships. In summary, bivariate Granger causality tests show that the FDAX unidirectionally Granger-causes the ODAX and the ODAX Granger-causes the DAX. This finding is entirely consistent with those in FOW. In addition, there is a bidirectional Granger causality between the DAX and the FDAX and the relationship is similar, suggesting that both the DAX and the FDAX are equally important in the price discovery process. The DAX and the ODAX bidirectionally Granger-cause each other. However, the DAX is dominant in the causality relationship, as evidenced by higher R^2, larger parameters estimated and the larger EC term in the VECM when the DAX is the dependent variable.

3.6.4 Multivariate Granger Causality

The discussion in the previous section deals in a bivariate framework. The objective is to isolate the effects of one security, such that more insight about the lead-lag relationship among the DAX securities can be made under a Multivariate case. Note that the system is cointegrated with two cointegrating vectors. Thus, error correction terms must be added according to the Granger Representation Theorem. To test for the multivariate Granger causality relationship, the following VECM is used:

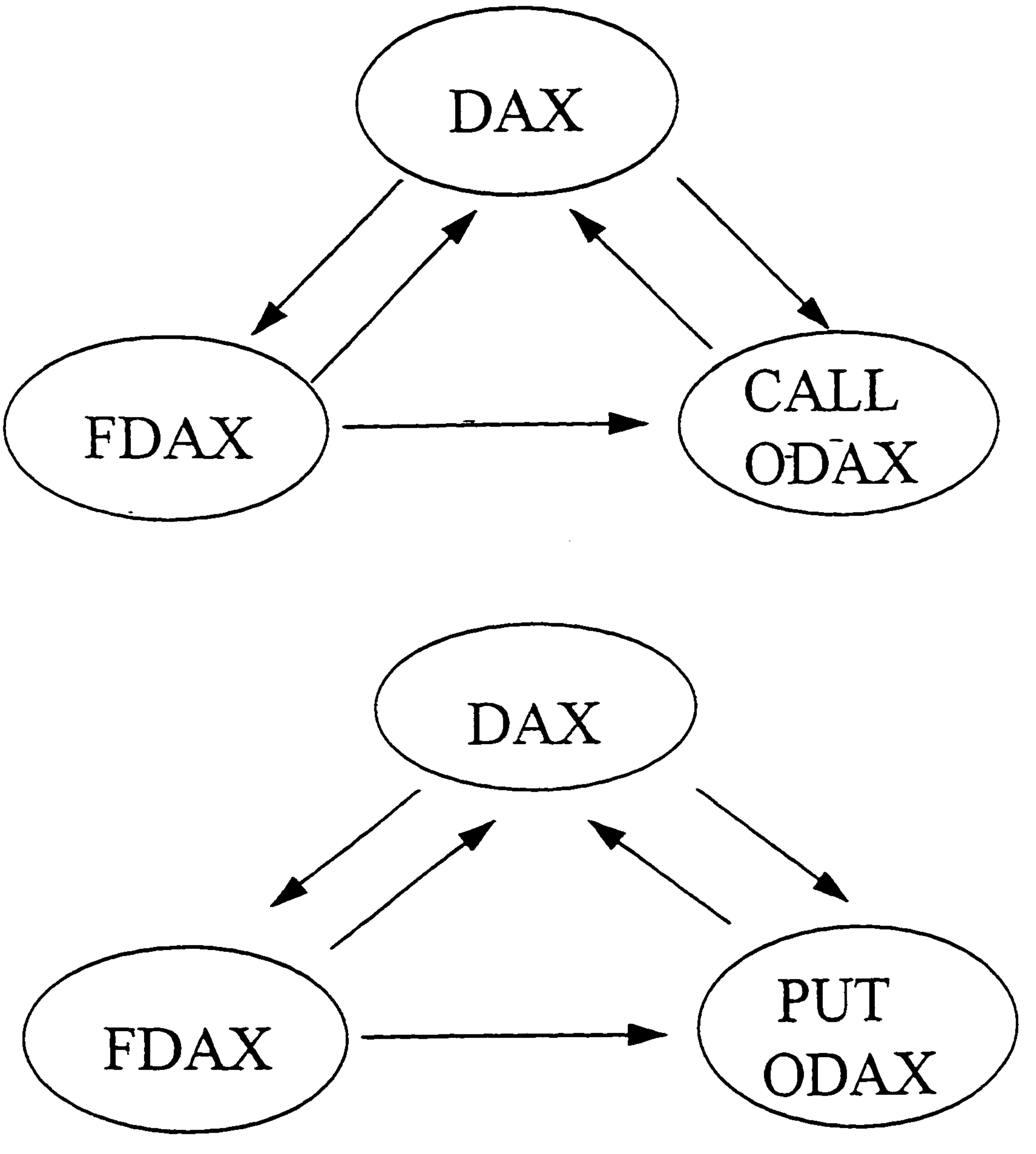

Figure 3.1

Results of Bi-Variate Granger Causality Tests Among the DAX Securities
Arrows denote causality relationships.

$$\Delta DAX_t = a_{10} + a_{11}\Delta DAXt\text{-}1 + a_{12}\Delta FDAX_{t-1} + a_{13}\Delta ODAX_{t-1} + d_{11}(DAX_{t-1} - FDAX_{t-1}) + d_{22}(DAX_{t-1} - ODAX_{t-1}) + \epsilon_{1t}, \quad (3.24a)$$

$$\Delta FDAX_t = b_{10} + b_{11}\Delta DAX_{t-1} + b_{12}\Delta FDAX_{t-1} + b_{13}\Delta ODAX_{t-1} + d_{21}(FDAX_{t-1} - DAX_{t-1}) + d_{22}(FDAX_{t-1} - ODAX_{t-1}) + \epsilon_{2t}, \quad (3.24b)$$

$$\Delta ODAX_t = c_{10} + c_{11}\Delta DAX_{t-1} + c_{12}\Delta FDAX_{t-1} + c_{13}\Delta ODAX_{t-1} + d_{31}(ODAX_{t-1} - DAX_{t-1}) + d_{32}(ODAX_{t-1} - FDAX_{t-1}) + \epsilon_{3t}. \quad (3.24c)$$

To account for possible heteroscedasticity and autocorrelation in the error term, the GMM estimation is employed here.[16]

Results of the multivariate Granger causality tests are given in Table 3.8. For the MINSPAN and REPLACE ALL procedures, the results are qualitatively the same. The following discussions are based on the REPLACE ALL procedure.

First, consider model (3.24a) in which return of the DAX is the dependent variable, lags of returns of the DAX, the FDAX and ODAX1 are the independent variables. Parameters a_{12} and a_{13} are significant, indicating that past returns of FDAX and ODAX Granger-cause the DAX. Note that the magnitude of a_{12} (0.047233) is larger than that of a_{13} (-0.011714). Their respective standardized values (normalized by standard errors) are 4.762687 and -3.465, which suggest that the FDAX has a more prominent effect in the causality relationship of the DAX than with the ODAX. When put option (ODAX4) is included in the model, the forecasting power of option vanishes. The parameter a_{13} is not significant, indicating no forecasting ability from past put option prices. This result is somehow counter intuitive, since puts and calls are closely related through the put-call parity. Nevertheless, results in a bivariate case show that put ODAX

[16] Results from Ordinary Least Squares (OLS) are qualitatively the same and not reported here.

Table 3.8

Results of Multivariate Granger Causality Test

Panel A: MINSPAN Procedure with Call ODAX

Parameter Estimated	ODAX1	ODAX2	ODAX3
a_{10}	-2.458E-05*	-2.327E-05*	-2.405E-05*
b_{10}	3.108E-05**	3.110E-05**	3.152E-05**
c_{10}	-4.092E-05	-4.834E-05**	-3.109E-05
d_{11}	-4.052E-03***	-3.825E-03***	-3.776E-03***
d_{12}	-1.966E-02***	-1.747E-02***	-1.343E-02***
d_{21}	-3.366E-03	-3.114E-03	-2.360E-03
d_{22}	3.610E-04	1.097E-04	-7.003E-04
d_{31}	-5.108E-01***	-2.707E-01***	-1.616E-01***
d_{32}	3.574E-03	-2.113E-03	-3.010E-03
a_{11}	2.176E-02	1.833E-02	1.808E-02
a_{12}	5.126E-02***	5.134E-02***	5.140E-02***
a_{13}	-1.241E-02***	-9.263E-03*	-8.351E-03**
b_{11}	7.055E-02***	6.997E-02***	7.204E-02***
b_{12}	-5.751E-02***	-5.842E-02***	-5.821E-02***
b_{13}	-2.566E-04	1.388E-03	-1.004E-03
c_{13}	-4.453E-02	9.730E-02***	1.398E-01***
c_{12}	2.605E-01***	2.483E-01***	2.269E-01***
c_{13}	-1.806E-01***	-3.208E-01***	-3.701E-01***

Panel B: MINSPAN Procedure with Put ODAX

Parameter Estimated	ODAX4	ODAX5	ODAX6
a_{10}	-2.464E-05**	-2.486E-05**	-2.196E-05
b_{10}	3.053E-05**	2.946E-05**	2.907E-05*
c_{10}	-2.741E-04***	-2.755E-04***	-4.039E-04***
d_{11}	-3.923E-03***	-3.874E-03***	-3.670E-03***
d_{12}	-7.494E-03***	-5.574E-03***	-5.435E-03**
d_{21}	-4.431E-03	-6.281E-03*	-5.245E-03
d_{22}	1.450E-03	3.382E-03	2.349E-03
d_{31}	-6.885E-01***	-5.464E-01***	-3.765E-01***
d_{32}	-1.280E-02***	-1.879E-02***	-2.837E-02***
a_{11}	1.431E-02	1.314E-02	1.384E-02
a_{12}	5.240E-02***	5.206E-02***	5.249E-02***
a_{13}	-3.185E-03	-1.428E-03	-2.358E-03
b_{11}	5.606E-02***	5.520E-02***	5.624E-02***
b_{12}	-4.896E-02***	-4.951E-02***	-4.960E-02***
b_{13}	1.951E-03	3.722E-03	2.965E-03
c_{11}	-1.266E-01***	-6.027E-03	1.133E-01***
c_{12}	2.885E-01***	2.613E-01***	2.705E-01***
c_{13}	-1.017E-01***	-1.882E-01***	-2.743E-01***

(table cont'd.)

Panel C: REPLACE ALL Procedure with Call ODAX			
Parameter Estimated	ODAX1	ODAX2	ODAX3
a_{10}	-2.444E-05*	-2.316E-05*	-2.385E-05*
b_{10}	3.051E-05**	3.062E-05**	3.096E-05**
c_{10}	-3.806E-05	-4.618E-05**	-3.117E-05
d_{11}	-4.023E-03***	-3.788E-03***	-3.731E-03***
d_{12}	-2.064E-02***	-1.794E-02***	-1.363E-02***
d_{21}	-2.578E-03	-2.271E-03	-2.002E-03
d_{22}	-3.692E-04	-6.849E-04	-1.009E-03
d_{31}	-5.044E-01***	-2.686E-01***	-1.612E-01***
d_{32}	3.734E-03	-1.942E-03	-2.955E-03
a_{11}	2.528E-02	2.132E-02	2.079E-02
a_{12}	4.723E-02***	4.723E-02***	4.763E-02***
a_{13}	-1.171E-02***	-7.931E-03	-6.993E-03 *
b_{11}	7.266E-02***	7.190E-02***	7.345E-02***
b_{12}	-6.348E-02***	-6.446E-02***	-6.391E-02***
b_{13}	1.665E-03	3.573E-03	1.443E-03
c_{11}	-3.482E-02	9.842E-02***	1.367E-01 ***
c_{12}	2.543E-01***	2.419E-01***	2.269E-01***
c_{13}	-1.847E-01***	-3.179E-01***	-3.679E-01***

Panel D: REPLACE ALL Procedure with Put ODAX			
Parameter Estimated	ODAX4	ODAX5	ODAX6
a_{10}	-2.384E-05**	-2.411E-05**	-2.132E-05
b_{10}	2.983E-05**	2.907E-05**	2.876E-05*
c_{10}	-2.909E-04***	-2.803E-04***	-4.009E-04***
d_{11}	-3.793E-03***	-3.759E-03***	-3.563E-03***
d_{12}	-7.177E-03***	-5.644E-03***	-5.454E-03***
d_{21}	-4.696E-03	-5.892E-03*	-4.987E-03
d_{22}	1.767E-03	3.026E-03	2.119E-03
d_{31}	-6.627E-01***	-5.440E-01***	-3.748E-01***
d_{32}	-1.502E-02***	-1.910E-02***	-2.802E-02***
a_{11}	1.205E-02	1.081E-02	1.242E-02
a_{12}	5.497E-02***	5.493E-02***	5.537E-02***
a_{13}	-2.523E-03	-1.183E-03	-2.786E-03
b_{11}	5.570E-02***	5.488E-02***	5.586E-02***
b_{12}	-4.858E-02***	-4.880E-02***	-4.885E-02***
b_{13}	1.764E-03	2.880E-03	2.242E-03
c_{11}	-9.521E-02**	4.502E-03	1.231E-01***
c_{12}	2.715E-01***	2.534E-01***	2.610E-01***
c_{13}	-1.137E-01***	-1.864E-01***	-2.720E-01***

*** Significant at 1%, ** Significant at 0.5%, *** Significant at 0.1%**

Granger-cause the DAX. The above result suggests that the FDAX is dominant over the put option in the causality relationship.

Second, since the error correction terms, d_{11} and d_{12}, are highly significant, they show that the DAX reacts to price disparities between the FDAX and the DAX and that between the DAX and the ODAX. Similar to the analysis under a bivariate case, HL is used to examine the speed of adjustments to shocks in other markets. The HL analysis under the mulitvariate framework is presented in Table 3.9. The HL of a FDAX shock is 171.95 periods while that of an ODAX is only 33.24 periods. That means, the DAX reacts to disparity between the DAX and the ODAX much quicker than that between the DAX and the FDAX. This result is consistent with the fact that the DAX and the ODAX are cointegrated, but there is no cointegrating relationship between the DAX and the FDAX. Note that the parameter estimated for call options is larger than that for put options. For example, d_{12} for ODAX is -0.02064 while that for ODAX4 is -0.007127. This is also consistent with earlier findings that put options play a relative minor role in the forecasting the return of the DAX.

For the case of the FDAX, similar results to those under the bivariate case are obtained. Again, the DAX and the FDAX Granger-cause each other. The magnitudes of the parameters a_{12} and b_{12} are similar, suggesting that the causality relationship is about the same. The only difference is that here an error correction term is included. However, the parameter d_{21} is not significant, which means that the FDAX does not respond to disparity between the DAX and the FDAX. This finding further suggests that the FDAX is the main driving force in the price discovery process among the DAX securities.

Table 3.9

Analysis of Half Lives of Multivariate Granger Causality Tests

Panel A: MINSPAN Procedure with Call ODAX							
		ODAX1		ODAX2		ODAX3	
Equation	Coefficient	Value of EC Term	Half Live	Value of EC Term	Half Live	Value of EC Term	Half Live
(3.24a)	d11	-4.052E-3	170.72	-3.825E-3	180.87	-3.776E-3	183.22
(3.24a)	d12	-1.966E-2	34.91	-1.747E-2	39.33	-1.343E-2	51.27
(3.24b)	d21	-3.366E-3	205.58	-3.114E-3	222.24	-2.360E-3	293.36
(3.24b)	d22	3.610E-4	1919.73	1.097E-4	6318.22	-7.003E-4	989.44
(3.24c)	d31	-5.108E-1	0.98	-2.707E-1	2.22	-1.616E-1	3.94
(3.24c)	d32	3.574E-3	193.60	-2.113E-3	327.69	-3.010E-3	229.93

Panel B: MINSPAN Procedure with Put ODAX							
		ODAX4		ODAX5		ODAX6	
Equation	Coefficient	Value of EC Term	Half Life	Value of EC Term	Half Live	Value of EC Term	Half Live
(3.24a)	d11	-3.923E-3	176.34	-3.874E-3	178.58	-3.670E-3	188.52
(3.24a)	d12	-7.494E-3	92.15	-5.574E-3	124.01	-5.435E-3	127.19
(3.24b)	d21	-4.431E-3	156.08	-6.281E-3	110.01	-5.245E-3	131.81
(3.24b)	d22	1.450E-3	477.69	3.382E-3	204.61	2.349E-3	294.74
(3.24c)	d31	-6.885E-1	0.73	-5.464E-1	0.92	-3.765E-1	3.37
(3.24c)	d32	-1.280E-2	53.81	-1.879E-2	36.54	-2.837E-2	24.09

Panel C: REPLACE ALL Procedure with Call ODAX							
		ODAX1		ODAX2		ODAX3	
Equation	Coefficient	Value of EC Term	Half Live	Value of EC Term	Half Live	Value of EC Term	Half Live
(3.24a)	d11	-4.023E-3	171.95	-3.788E-3	182.64	-3.731E-3	185.43
(3.24a)	d12	-2.064E-2	33.24	-1.794E-2	38.29	-1.363E-2	50.51
(3.24b)	d21	-2.578E-3	268.52	-2.271E-3	304.87	-2.002E-3	345.88
(3.24b)	d22	-3.692E-4	1877.08	-6.849E-4	1011.69	-1.009E-3	686.62
(3.24c)	d31	-5.044E-1	0.99	-2.686E-1	2.24	-1.612E-1	3.95
(3.24c)	d32	3.734E-3	185.28	-1.942E-3	356.58	-2.955E-3	234.22

(table cont'd.)

Panel D: REPLACE ALL Procedure with Put ODAX							
		ODAX4		ODAX5		ODAX6	
Equation	Coefficient	Value of EC Term	Half Live	Value of EC Term	Half Live	Value of EC Term	Half Live
(3.24a)	d11	-3.793E-3	182.40	-3.759E-3	184.05	-3.563E-3	194.19
(3.24a)	d12	-7.177E-3	96.23	-5.644E-3	122.47	-5.454E-3	126.74
(3.24b)	d21	-4.696E-3	147.26	-5.892E-3	117.30	-4.987E-3	138.64
(3.24b)	d22	1.767E-3	391.93	3.026E-3	228.72	2.119E-3	326.76
(3.24c)	d31	-6.627E-1	0.75	-5.440E-1	0.92	-3.748E-1	4.41
(3.24c)	d32	-1.502E-2	45.80	-1.910E-2	35.94	-2.802E-2	24.39

Apart from finding a bidirectional causality relationship between the DAX, the FDAX does not have any causality relationship with the ODAX, should puts or calls are used in the VECM. Furthermore, the error correction term d_{22} is not significant either. It suggests that the FDAX does not react to disparity between the ODAX in a previous period. At a first glance, these statistics mean that the ODAX is dormant in forecasting the future returns of the FDAX. However, the synchronous relationships among the three index securities do not preclude the flow of information from the ODAX to the FDAX. Since the ODAX Granger-causes the DAX and the DAX Granger-causes the FDAX, there exists an indirect causality relationship between the FDAX and the ODAX, though there is no significant direct causality relationships.

Since the put and calls exhibit different patterns, the analyses here are separated into two groups. For the call ODAX, there is some evidence that the DAX Granger-causes the ODAX, though the parameter c_{11} under the case of using implied volatilities of past fifteen minutes is not significant. The FDAX also Granger-causes the ODAX. Nevertheless, the only significant error correction term happens to be the disparity between the DAX and the ODAX. Differences between the FDAX and ODAX in a previous period do not add power in forecasting future returns of the ODAX. One interesting point to note is that the magnitude of the error correction term in model (3.24c) is larger than that in model (3.24a). It suggests that the ODAX reacts more quickly to disparity between the DAX and the ODAX. This implies that the DAX provides more information in the pricing relationship than the reverse case.

For the put ODAX, there is some evidence that the DAX Granger-causes the ODAX, though the parameter c_{11} for using implied volatilities of past hour is not significant. The parameter c_{12} is significant under different estimates of implied volatilities, suggesting that the FDAX Granger-causes put ODAX. Interestingly, both error correction terms d_{31} and d_{32} are highly significant, suggesting that put ODAX reacts to disparities between the DAX and FDAX. This finding is in contrast with that of call ODAX, which does not respond to the price disparity between FDAX and call ODAX. Nevertheless, the parameter d_{32} is smaller than d_{31} in magnitude, which means that the DAX is more useful in correcting price disparity. Given that there is cointegration between the DAX and the ODAX while no cointegration occurs between the FDAX and the ODAX, this result is not surprising.

A comparison between the bivariate and multivariate causality results is given in Table 3.10. Most of the results under the bivariate case still hold under the multivariate case. The only exception is that put ODAX Granger-causes DAX under the bivariate case but not under the multivariate case. As discussed earlier, it suggests that the FDAX dominates the put ODAX in the lead-lag relationship of returns of the DAX.

The above discussions are summarized in Figure (3.2). Similar to Figure (3.1), the arrows in this figure also denote the causal relationships. To conclude, both bivariate and multivariate Granger causality test results suggest that the DAX and the FDAX are the dominant securities in the price discovery process. Though the role of ODAX is relatively minor, it is not 100% redundant, as evidenced by its role in the VECM, the finding that the ODAX Granger-causes the DAX and the indirect causal relationship

Table 3.10

Comparison of Results of Bivariate and Multivariate Granger Casuality

Bivariate Results	Multivariate Results
DAX GC FDAX	DAX GC FDAX
DAX GC Call ODAX	DAX GC Call ODAX
DAX GC Put ODAX	DAX GC Put ODAX
FDAX GC DAX	FDAX GC DAX
FDAX GC Call ODAX	FDAX GC Call ODAX
FDAX GC Put ODAX	FDAX GC Put ODAX
Call ODAX GC DAX	Call ODAX GC DAX
Call ODAX does not GC FDAX	Call ODAX does not GC FDAX
Put ODAX GC DAX*	Put ODAX does not GC DAX*
Put ODAX does not GC FDAX	Put ODAX does not GC FDAX

* The only difference in results. See text for definitions of variables.

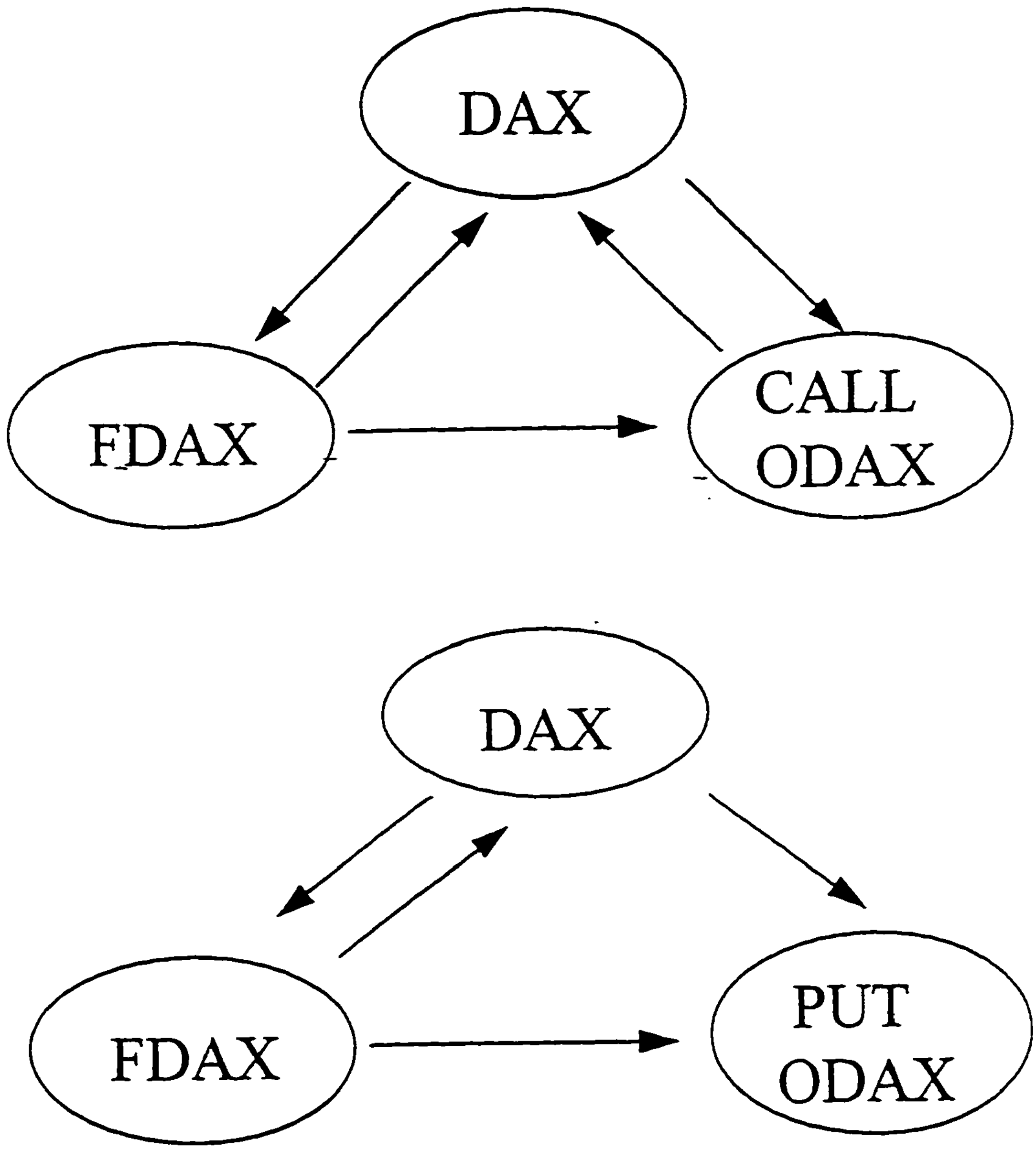

Figure 3.2

Results of Multivariate Granger Causality Tests Among the DAX Securities
Arrows denote causality relationships.

between the FDAX and the ODAX. Given the above analysis, it is concluded that there are feedback relationships among the three securities and these securities are contemporaneous related. Results from multivariate Granger-causality tests show that there are flows of information from one security to another. The three securities are informationally linked together.

3.6.5 Information Sharing

Table 3.11 presents the results of the GG information sharing model for the REPLACE ALL procedure with ODAX1. Results of other procedures are qualitatively the same and are not reported.

The common factor here can be considered as the unobservable efficient price common to the three DAX securities. The contributions of the three DAX securities in price discovery are given by the vector $\alpha_{\perp}$'. First, an examination of $\alpha_{\perp}$' shows that the DAX has the highest weight in the common factor. The weight of FDAX is similar, while that of the ODAX is the lowest. That means, from the perspective of information sharing, the DAX and the FDAX contribute most to the price discovery process while the ODAX does not contribute much. In other words, the largest sources of information come from the index and index futures. From the persepctive of information processing, this finding implies that the options market performs a minor role in price discovery. Another important observation is that the weights of DAX and the FDAX are very similar, which shows that the index itself and index futures are essentially equal in the degree of information sharing.

Table 3.11

Results of Gonzalo-Granger Information Sharing

Panel A: Weights of the DAX Securites in the Common Factor			
	Security		
	DAX	FDAX	ODAX
$\alpha'\perp$	1.00	0.94909	0.04024

Panel B: GG Test Statistics			
	Security		
	DAX	FDAX	ODAX
H_0: X_i is not in the common factor	2208.7 (0.00)	2308.7 (0.00)	6.937 (0.00844)

P-values are in parentheses.

The above analysis only examines the degree of contribution to price discovery among the DAX securities. To formally test the importance of each security in the common factor, the χ^2 (1) test under the null of that security is the sole component in the common factor is done. Note that the test statistics are highly significant for the DAX and the FDAX. The χ^2 statistic for testing the null that the DAX is the only component in the common factor is 2208.7, while that for the FDAX is 2308.7, both of them are significant at 0.1%. Thus, the null hypotheses of having the DAX or the FDAX as the sole component in the common trend are rejected. In other words, both the DAX and the FDAX are in the common factor. From the information processing perspective, it means that both the DAX and the FDAX contribute to the price discovery process. The test statistic for the null hypothesis of having the ODAX as the only component in the common factor is 6.937, which is much smaller than those of the DAX and the FDAX and is only significant at the 1% level. Given the large number of observations used here, 1% significance level is not appropriate (the Lindley's Paradox discussed in Chapter 1). Therefore, the null hypothesis is not rejected. This means that the ODAX is not in the common trend. Consequently, the ODAX does not contribute to the unobservable efficient price of the DAX securities.

To conclude, the DAX and the FDAX appear to have more contribution in the price discovery process, as evidenced by their heavy weights in $\alpha_{\perp}'$, and significant GG test statistics. The ODAX appears to be a redundant asset in discovering new information.

3.7 Summary

In this chapter, the price discovery process among the DAX securities is examined. Based on the results of Granger causality tests and information sharing models, it is found that the FDAX is the main driving force in the price discovery process, the DAX is second and the ODAX contributes least.

Chapter 4

Intraday Volatility Transmissions in Index Securities: Evidence From The German Markets

4.1 Introduction

This chapter investigates the intraday behaviors of volatilities of the stock index, index futures and index options (hereafter the index securities). Chapter 3 of this dissertation examines the intraday information processing mechanism of the index securities through the first moment (price discovery). In this chapter, further evidence in information processing is given through the second moment (volatility transmissions). The study of volatility transmissions is important since volatility is also a source of information (Ross (1989)). The examination of volatility transmissions, together with the price discovery process in Chapter 3, will provide a more comprehensive understanding about the intraday information processing mechanism among the index securities.

Early works on volatilities in derivatives markets mainly concentrate on the impacts of futures trading on volatilities of the spot markets, e.g., Bortz (1984) and Simpson and Ireland (1986). These earlier works, however, suffer from problems in data and econometric techniques (to be discussed in the next section). One recent focus in the study of volatility transmissions in financial markets is the volatility spillover process, in which the volatility of one market affects those of other markets.

The study of volatility spillovers is enhanced with advances in econometric techniques, and there are more robust estimations of the volatility spillover process. For example, the Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) model developed by Nelson (1991) can be used to model the asymmetric

impacts of good and bad news on volatilities. Applying the EGARCH model, Koutmos and Booth (1995) find that there exists asymmetric impacts of volatilities among the New York, London and Japan equity markets; Booth, Martikainen and Tse (1997) provide evidence on asymmetric impacts of volatilities among the Danish, Norwegian, Swedish and Finnish stock markets. Apart from the highly celebrated EGARCH model, other techniques in the study of volatility spillovers are also available. For example,, Chowdhury, Martikainen and Tse (1996b) apply the Extreme Value Vector Autoregression (EV-VAR) approach to study intraday volatility spillovers among stock index futures markets in New York, London and Tokyo.

Specifically, several issues are addressed in this chapter: (i) whether volatilities of the derivative markets lead the volatility of the spot market; (ii) whether the derivatives and the stock index markets share a common volatility process; and (iii) whether good and bad news have asymmetric impacts on the volatility spillover processes among the index securities.

4.2 Literature Review

Under an efficient market, information derived from one market will be incorporated into the pricing function of another market, if the two markets are interdependent in certain degrees. As financial markets are increasingly integrated, their interrelationships are not only through the return, the mean (the first moment), of the pricing function.[1] According to Ross (1989), higher volatility means more information.

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[1] Interdependence of volatilities across financial markets does not necessarily mean market inefficiency.

It is because investors can only profit the information from trading. Information releases will induce then trading and trading will lead to higher variances. The relationships between volatilities across markets, the variances (the second moment), are as informative as the first moment.

Early studies of volatility in derivative markets concentrate on the impacts of futures tradings on spot volatility. Such early evidence usually supports the notion that futures tradings do not necessarily lead to higher volatilities in the spot markets. For example, Simpson and Ireland (1982) study the impacts of trading of futures contracts on Government National Mortgage Association (GNMA) pass-through certificates on the volatility of cash market of the GNMA securities. Using multivariate time series analysis and regression analysis, they find that tradings in GNMA futures do not affect the volatility of cash prices of GNMA certificates, either on a daily or weekly basis. Bortz (1984) studies the impact of T-Bond futures on the volatility of the T-Bond cash market. Though there is evidence that the T-Bond futures tend to lower the volatility of the T-Bond cash market, Bortz (1984) concludes that futures tradings due to speculations may also destablize cash prices in the wake of periodic news releases. These excessive speculative volatilities may spillover into the cash markets. Note that the destablization of cash prices is due to speculations, not futures tradings.

Gerety and Mulherin (1991) show that there is no systematic increase in volatility, intraday or otherwise, in stock index since the introduction of index futures. One interesting observation is that in the 1930s, even without index futures, there was higher volatility. Gerety and Mulherin (1991) argue that the apparent higher volatility is due

to speculation rather than futures tradings. Edwards (1988) studies the advent of stock index and interest rates futures on the volatilities of the spot stock index and interest rates. He concludes that futures do not lead to higher volatilities in the cash markets. Thus, the main conclusion from extant literature is that the introduction of financial futures has not destabilized or increased the volatilities of the cash markets. Increases in volatilities may be due to speculations but not the advent of financial futures.

However, these early works on volatility only study the impacts of futures tradings on spot volatilities. They do not address the issue whether volatility in one market affects that of another market. Thus, there are no considerations of volatilities across markets. Furthermore, these works also suffer from problems in data and the techniques used. First, these studies typically use daily or even weekly data. In other words, intraday volatilities are ignored. Ignoring intraday volatilities may make the analysis not as rich as it could be since changes in volatilities may occur within the day rather than between the days. Second, the econometric techniques used do not take into account of autocorrelation and heteroscedasticity. As shown in Chapter 2, the variance of returns of the DAX securities follow ARCH processes. Without taking into account the ARCH/GARCH effects will undermine the conclusions reached.

It is not until recent developments in time series techniques, especially the advent of GARCH models, that the study of volatility spillovers among financial markets becomes more important and starts to appear in the literature. In the literature, volatility spillovers are studied in extant in cross-markets securities tradings. For example, Hamao, Masulis and Ng (1990) study volatility spillovers among equity markets in New

York, London and Tokyo; Lin, Engle and Ito (1994) examine volatility spillovers between the New York and Tokyo markets; Tse and Booth (1996) investigate volatility spillovers between T-Bill and Eurodollar futures; Booth, Chowdhury, Martikainen and Tse (1996b) explore volatility spillovers among stock index futures markets in the United States (U.S.), the United Kingdom (U.K.), and Japan; Booth, Martikainen and Tse (1997) analyze the asymmetric effects in volatility spillovers in the Scandinavian countries through the EGARCH model. Bae and Karolyi (1994) employ different GARCH models to study the asymmetric effects of good and bad news on the volatilities of the U.S. and Japan markets. They conclude that asymmetric models are better in capturing the information transmission process. Koutmos and Booth (1995) use the EGARCH model to study volatility transmissions among the New York, London and Tokyo stock markets. They find that there exists asymmetric effects in the volatility spillover process. Negative (unfavorable) news tends to have a greater impact than positive (favorable) news.

The general conclusion of these studies in volatility spillovers is that volatility in one market (for example, the U.S.) will affect the volatility of another market (for example, Japan). In addition, there are asymmetric effects in the process of volatility spillovers. Negative news tends to have greater impacts on volatilities than positive news. Though there are considerable amount of works in the study of volatility spillovers across different national markets, little is done to explore volatility spillovers in domestic

derivatives. Those address the issue of volatilities among domestic derivatives often study the lead-lag relationships between volatilities of these instruments.[2]

For example, Kawaller, Koch and Koch (1990) examine the lead-lag relationships between the intraday volatilities of the Standard & Poor (S&P) 500 index and the S&P 500 index futures. Using volatilities of 30 minute returns, they show that intraday volatility of the S&P 500 futures is higher than that of the S&P 500 index. However, there is no systematic pattern of index futures (index) volatility leading index (index futures) volatility through Granger causality tests. This implies that volatility of the futures (spot) market contains no forecasting ability about the future volatility of the spot (futures) market. However, one particular point to note is that intraday or daily volatility of index futures is much higher than that of the stock index. In the framework of Ross's (1989) information-volatility hypothesis, results of Kawaller et al. (1990) imply that though the volatility of futures cannot be used to forecast the volatility of the spot index, more information (higher variance) is embedded in the futures.

However, a recent study by Crain and Lee (1995) (CL) provides contrary evidence. CL examine the impacts of scheduled macroeconomic announcements on the volatilities of spot and futures markets in interest and exchange rates. They show that volatility of futures Granger-causes volatility of the spot market on both announcement and non-announcement days, but not the other way. These results mean that volatility is transmitted from the futures market to the spot market. Under the framework of Ross

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[2] Koutmos and Tucker (1996) is one of the few studies that address volatility spillovers among domestic securities. More discussions on volatility spillovers in domestic securities are given below.

(1989), results in CL imply that futures market helps discover new prices more prominently. CL attribute the superiority of futures in discovering new information to the high liquidity and the ease of trading in futures market. These advantages of futures markets allow market participants to react more quickly to new information. This argument is also consistent with the empirical findings of the trading cost hypothesis posited in Fleming, Ostdiek and Whaley (1996). Thus, from the persepctive of volatiltiy, the futures market is also more efficient in information processing.

The difference in results between CL and Kawaller et al. (1990) is asset specific. While CL study interest and exchange rates futures, Kawaller et al. (1990) examine the stock index futures. However, all the above mentioned studies only focus on volatilities between two assets: those of futures and the underlying asset. Volatilities of options and other derivatives are left out in the lead-lag relationships. In this study, this issue is re-examined by incorporating volatilities of index options into the analyses.

Since futures and options are derivatives, options may also reveal information about the underlying asset just as futures do. Black (1975) proposes that informed traders may prefer to trade options rather than shares due to economic incentives like lower transaction costs and higher leveraged effects. Empirically, Manaster and Rendleman (1982) show that options may contain information up to twenty four hours before the information is reflected in stock prices. Anthony (1988) applies Granger causality tests and find that trading volume of options tends to lead trading volume of stocks with one day lag. Under Copeland's (1976) hypothesis that trading volume can proxy for the rate of information arrival, Anthony's (1988) results imply that there is a

sequential flow of information from the options market to the stock market. Thus, from an information point of view, these works show that option markets are more efficient than the spot market in information processing.

Volatility, as contained implicitly in the prices of options on a market index, provides one measure of anticipated variability of market returns for the longer term. These anticipated volatilities are known as implied volatilities and they provide ex-ante estimates of future variabilities from market participants. Han and Misra (1990) use data on S&P 500 Index call options and S&P 500 future options (options on futures) to imply the volatilities of the S&P 500 Index and the S&P 500 Index futures. They find that prior to the 1987 Stock Crash, the magnitude of implied volatility of index futures is similar to that of the index. However, index futures become more volatile than the stock index after the 1987 Stock Crash. Nevertheless, no formal analysis on the lead-lag relationships between volatilites is made.

More recently, Kawaller, Koch and Peterson (1994) re-address the issue of lead-lag relationships between historic volatilities and implied volatilities. Using futures data on S&P 500 index, Deutschemark, Eurodollar and live cattle (in which they argue that the results should be applied to a wide range of futures contracts) and their corresponding future options in the last quarter of 1988, they find that the implied volatilities of future options do not lead the historical volatilities of futures. This means that option traders cannot forecast impending volatility changes reliably. In other words, option traders are more likely to respond to previous intraday short term volatility conditions in the

underlying markets (the futures contracts) rather than to anticipate future variabilities in the underlying markets.

Recently, volatility spillovers among domestic derivatives markets are being explored. Koutmos and Tucker (1996) (KT) study the temporal relationships between volatilities in stock index and index futures markets through the EGARCH model. Using daily data from April 1, 1984 to December 31, 1993, they find that innovations from the futures market affect the volatility of the stock market in an asymmetric fashion. Bad news (negative innovations) in the futures market tend to increase volatility of the spot market more than good news (positive innovations). However, innovations in the stock market do not affect the volatility of the futures market. That means, from an information processing perspective, the index futures market is more efficient than the cash market since volatility of futures affect that of the spot but not the other way. However, KT can be criticised in two ways. First, they use daily data. Thus, intraday volatility spillovers are ignored. Since spot and futures are traded contemporaneous, daily closing prices may not be a good estimate of the volatility relationship. Second, their study is a two asset case; other index securities are left out in the analysis. This dissertation extends KT by examining the intraday volatilities of three index securities.

Apart from the volatility spillover process, another related issue is whether these index securities share a common volatility process. Examining the presence of a common volatility process is useful since this is related to the information transmission mechanism. Finding a common volatility process among the index securities would mean

their second moments are related, which implies that information from one market will be incorporated into the pricing function of the other market.

A feature is said to be common if a linear combination of the series does not contain the feature although individual data series has the feature. In this study the common feature to be tested is ARCH.[3] If returns of individual index security exhibit ARCH effects and a linear combination of the returns of index securities does not, then there exists a common volatility process among the index securities. In this way, the concept of common volatility is very similar to that of cointegration.

In the literature, Engle and Susmel (1993) find that there is a common volatility process for several stock markets for the period 1980-1989. More recently, Booth, Chowdhury and Martikainen (1996a) document that the U.S., the U.K. and the Japanese stock index futures markets share a single common volatility process; Tse and Booth (1996), however, find that there is no common volatility in the U.S. and Eurodollar interest rates.

Apart from these studies on common volatilities among different national markets, Arshanapalli and Doukas (1994) study the existence of common volatility in the S&P 500 index futures and the S&P 500 index. Using the ARCH testing procedure developed by Engle and Kozicki (1993), they find that for the sample period of October 1987, index future and cash stock markets do not share a common volatility process. That means, the second moments of the two markets are not related. Arshanapalli and Doukas (1994)

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3 In Chapter 2, it is shown that the index securities exhibit ARCH effects in their return series.

can be criticized in two ways. First, it is the sample period used. Though October 1987 is characterized by high and low volatility in the markets, the Stock Crash is an extreme event. The process of information processing may change after the Stock Crash due to institutional changes. Hence, the results in Arshanapalli and Doukas (1994) are only confined to one specific time period. This study improves the findings of Arshanapalli and Doukas (1994) by looking at a much longer post-Crash period. Second, though Arshanapalli and Doukas (1994) use intraday data to examine the existence of common volatility, they use data on five minute returns. As noted in Booth et al. (1996b), intraday (high frequency) data though contain more information, it also creates much noise in the data series. Such noise will introduce additional problems into the analysis - empirical results may capture effects of the noises rather than impacts of the information. To remedy these potential biases, a suitable time grid should be chosen so that a balance between information and noise can be made. This study also improves Arshanapalli and Doukas (1994) by providing results using different time intervals.

In this chapter, the lead-lag relationsips of volatilities among the index securites are first studied. Then the issue of whether common volatility exists among the index securities is examined. Finally, the effects of volatility spillovers in one market to another will be examined through the EGARCH and the EV-VAR models.

This study contributes to the literature in the following ways. First, this study will extend previous studies by using intraday transaction data. Though previous studies (namely KT) document asymmetric effects in the volatility spillover process in derivative markets, they only use daily data. Using closing data may induce additional biases into

the analysis since there exist a distinct "U-shaped" pattern in futures trading (Ekman (1992)). The use of intraday data in this study can mitigate such biases. Second, changes in volatility may occur within the day rather than between the days. Using daily data will not capture the effect of intraday changes in volatilities. Thus, intraday transaction data will give more insights into the changes in the volatility process. Third, this study will study the volatility spillover process among the three index securities (the DAX, the FDAX and the ODAX). Since one drawback of KT is that they just examine volatility spillover within a bivariate case, this study will extend KT by looking at a system of three index securities.

4.3 Data

4.3.1 Data Sources

Data of the DAX, FDAX and ODAX are obtained from the sources outlined in Chapter 3. Nearby FDAX contracts are used to calculate returns of the FDAX. Procedures of finding the implied values of the DAX from ODAX prices are same as those in Chapter 3. However, there are some differences in the construction of the return series. In chapter 3, since the focus is information sharing, a closely matched trade of the three index securities is necessary so that the problem of simultaneity can be corrected. Hence the MINSPAN and the REPLACE ALL procedures are used. In this chapter, the variance of returns of the index securities in fixed time intervals are used because the focus here is volatility.

The choice of time intervals reflects the balance between two considerations: information and noise. Since the DAX is updated every minute, the finest time interval

is one minute. However, volatility is defined as the variance of return, one minute interval is not feasible. On one hand, if a very fine (short) time interval is used, e.g., one minute interval, much noise will be introduced in the data series. Changes in security prices may reflect noises due to bouncing between the bid and ask prices, infrequent trading or simply from noise trading, rather than new information. On the other hand, a wide time interval will also mean the loss of information because the information will be fully reflected in prices within the time intervals. In this way, there may be no apparent effects on security prices because of rapid adjustments to new information. Keeping these two considerations (noies and information) in mind, data series of five-minute, 15-minute and 30-minute intervals are used to test the hypotheses.

The data collection procedures are as follows. First, the last observation in each time interval is taken as the observation in that interval (P_t) . If there is no observation for that interval, the price of the previous time interval (P_{t-1}) in the same day is used. If P_{t-1} is missing, then P_{t-2} is used and so on. If there is no valid data in the same day, the observation is regarded as missing. In doing this, an implicit assumption about no change in asset prices is made. This is a standard procedure in the literature and is labeled as the "Time Replacement Method" in this dissertation. However, this assumption is not without qualifications. The value of the underying asset may change but there are simply no trades to reflect such changes. In other words, there may still be a problem of infrequent trading.

Table 4.1 shows the distribution of missing values under alternative data collection procedures. Clearly there is a tradeoff between the number of observations

Table 4.1

Number of Missing Observations Under Alternative Data Collection Procedures

	Data Collection Procedures		
Securities	5-Min	15-Min	30-Min
DAX	44 (0.24)	13 (0.21)	6 (0.19)
FDAX	35 (0.19)	5 (0.08)	2 (0.06)
ODAX	1157 (6.20)	44 (0.71)	8 (0.26)
Number of Observations	18648	6216	3108

5-Min refers to the five minute interval procedures and so on. Numbers in parentheses are percentage of missing values.

and the number of missing values under different data collection procedures. For example, if a five minute interval is used, there are 18,681 observations, but the number of missing values, hence "time replaced" by previous values, is also higher than those of the other two procedures. For the DAX and the FDAX, the problem of missing values is not that severe but it is a real problem for the ODAX. Less than 1% of the observations of the DAX and the FDAX are "time replaced" but over 6% of the ODAX values are missing. To test whether empirical results are sensitive to the data collection procedures, data series constructed under these alternative data collection procedures are used.

For the construction of volatility measures, variance of the minute-by-minute returns within a given time period is used. This comes the missing value problems. If missing prices are "time replaced" by previous observations, there will be a series of "artifical" zero variances. To test whether results are affected by how missing data are handled, both "time replacement" and non replacement measures of volatility are used.

Another way to construct the volatility measures is to employ the EV estimates of volatility. This is to be discussed in greater details in the next section.

4.4 Method of Analysis

4.4.1 Granger-Causality

Similar to that in Chapter 3, this chapter also use pair-wise Granger-causality tests to study whether the volatility in one market leads the volatility of the other market. The difference is that the data series are now volatilities in fixed time intervals. The following bivariate vector autoregressive (VAR) model is used:

$$\begin{bmatrix} V_{1t} \\ V_{2t} \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} + \begin{bmatrix} \Psi_{11}(L) & \Psi_{12}(L) \\ \Psi_{21}(L) & \Psi_{22}(L) \end{bmatrix} \begin{bmatrix} V_{1t} \\ V_{2t} \end{bmatrix} + \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \end{bmatrix}, \tag{4.1}$$

where $V_{i,t}$ (i=1,2) are the volatilities of the DAX, the FDAX and the ODAX at time t, Ψ_{ij}(L) (i,j = 1,2) are the coefficient matrices of the VAR, μ_i (i=1,2) are the constants of the VAR and ϵ_{it} (i=1,2) are the residuals. Coefficients in Ψ_{ij}(L) (i≠j) measure the impact of past volatilities in market i on that of market j. For example, $\Psi_{ij}(L) = \phi_1(L) + \phi_2(L^2) + \phi_3(L^3) + \ldots + \phi_k(L^k)$, where ϕ_{ij} are coefficients in $\Psi_{ij}(L)$, k is the number of lags in the VAR, and L is the lag operator. To test whether volatility of one index securities Granger-causes that of another, the following test statistic is calculated:

$$S = \frac{(SSE_0 - SSE_1)\ /\ p}{SSE_1\ /\ (T - 2p - 1)}, \tag{4.2}$$

where SSE_0 is the sum of squares of residuals under the restricted model in which coefficients of Ψ_{ij}(L) (i≠j) equal to 0; and SSE_1 is the sum of squares of residuals under the full model. The test statistic, S, is distributed as a χ^2 variate with p degress of freedom, where p is the number of lags in the VAR. If S is significant, then the null hypothesis of no casuality is rejected. The number of lags in the VAR model is determined by the Schwarz Information Criterion (SIC).[4]

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[4] $SIC(p) = \ln\ |\Sigma|\ + (\ln T/T)pM^2$, where p is the number of lags in the VAR, T is the number of observations, M is the dimension of the VAR, Σ is the mean squared error of the VAR. See Lüthepohl (1993) for details.

4.4.2 Testing for Common Volatility

Returns on assets are assumed to be generated by the following model:

$$r_t = m_t + \epsilon_t \ , \qquad (4.3)$$

where r_t is the p x 1 vector of observed asset returns, m_t is the p x 1 vector of time varying risk premia and ϵ_t is the p x 1 vector of unexpected components. The unexpected components can be further decomposed into two parts:

$$\epsilon_t = B f_t + e_t \ , \qquad (4.4)$$

where B is a p x k nonstochastic matrix, f_t is the k x1 vector of common factors and e_t is the p x 1 idiosyncratic components. Further assumptions are made:

$$E_{t-1} \ (f_t \, e_t') = 0 \ , \qquad (4.5)$$

$$E_{t-1} \ (f_t f_t') = \Sigma_{t\,(kxk)} \ , \qquad (4.6)$$

$$E_{t-1} \ (e_t e_t') = \Omega_{t\,(pxp)} \ . \qquad (4.7)$$

The variance-covariance matrices of f_t and e_t are Σ_t and Ω_t respectively. Economically, equations (4.5) to (4.7) require the idiosyncratic components and the common factor to

be uncorrelated. That means, the unexpected component in (4.4) is caused by two unrelated forces: market wide information (the common factors f_t) and asset specific information (e_t). Given these assumptions, the conditional variance of asset returns, V_{t-1} can then be written as:

$$V_{t-1} = B\,\Sigma_t\,B' + \Omega_t\,. \tag{4.8}$$

Following Engle and Susmel (1993) and Booth, Chowdhury and Martikainen (1996a), the following restrictions are made: k=1 and $\Omega_t = \Omega$. That means, no heteroskedascity in the idiosyncratic components and the number of common factors is set to be one. As put forward in Engle and Susmel (1993), " ... if the simple model (k=1 and $\Omega_t = \Omega$) is the true model, more general models might lead to overparametizations and inferences that are inefficient." Since the common factor interested is the ARCH effect, it is appropriate to set the above restrictions.

A common feature is said to exist if individual series exhibit a particular characteristic and a linear combination of the series will eliminate that characteristic. The common feacture to be tested here is the ARCH effect. If individual series exhibit ARCH effects and the ARCH effects vanish in a linear combination of these series, then the series are said to have a common volatility, namely the ARCH effect. In this way, the concept of common feature is very similar to that of cointegration.

The testing for common volatility follows a two-step process. First, returns of the DAX securities are tested for the presence of ARCH effects by Engle's Langrange

Multiplier (LM) test. If ARCH effects exist for the DAX securities, then portfolio return, $R_p = R_{DAX} + w_1 R_{FDAX} + w_2 R_{ODAX}$, is tested for ARCH effects.[5]

To test for ARCH effects in the portfolio, both the univariate ARCH (UARCH) and the multivariate ARCH (MARCH) tests are used. For the UARCH test, the square of R_p is regressed on the squares of lagged values of R_{DAX}, R_{FDAX}, and R_{ODAX}. For the MARCH test, square of R_p is regressed on the squares of lagged values of R_{DAX}, R_{FDAX}, and R_{ODAX}, and lagged values of cross product of R_{DAX}, R_{FDAX} and R_{ODAX}. Engle and Kozichi (1993) shows that the LM statistics equal to the minimum of T^*R^2, where T is the number of observations and R^2 are the coefficients of determination of the above regressions. Engle and Kozichi (1993) also show that the LM statistics are distributed as χ^2 variates with (p-1) degrees of freedom where p is the number of regressors. In this step, portfolio weights (w_1 and w_2) are chosen so that the test statistics is minimized. The iteration process starts with a pair of w_1 and w_2 within the parameter space of -50 to +50. A search algorithm is used to compare the TR^2 statistics under various weights (with increments of 0.01) until the minmium TR^2 statistic is found. If the TR^2 statistic is not significant, then there are no ARCH effects in the portfolio returns and hence a common volatility process exists.[6]

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[5] Note that both w_1 and w_2 do not equal to 0; and w_1 is the portfolio weight for the FDAX and w_2 is the portfolio weight for the ODAX. A negative weight means that the security is in short position. The weight of DAX is normalized to be one. For example, if $w_1 = 2$ and $w_2 = 3$, then 1/6 of the portfolio is invested in the DAX, 1/3 in the FDAX and 1/2 in the ODAX.

[6] Note that significance level of 0.1% is used for the five minute return series; 0.5% level is used for the 15 minute return series; and 1% level is used for the 30 minture return series. See the discussion on Lindley's Paradox in Chapter 1 for details.

4.4.3 EGARCH Model

Let R_{it} be the return at period t for market I and if follows the following VAR process:

$$R_{it} = \beta_{i0} + \sum_{j=1}^{3} \beta_{ij} R_{j,t-1} + \epsilon_{it} . \tag{4.9}$$

The multivariate EGARCH model used to describe volatility spillover is:

$$\sigma_{i,t}^2 = \exp\left(\alpha_{i,0} + \sum_{j=1}^{3} \alpha_{i,j} f_j(Z_{j,t-1}) + \gamma_i \ln(\sigma_{i,t-1}^2)\right), \tag{4.10}$$

for i,j = 1,2,3;

$$f_j(z_{j,t-1}) = \left(|Z_{j,t-1}| - E(|Z_{j,t-1}|) + \delta_j Z_{j,t-1}\right), \tag{4.11}$$

for j = 1, 2, 3 and

$$\sigma_{i,j,t} = \rho_{i,j}\, \sigma_{i,t}\, \sigma_{j,t} , \tag{4.12}$$

for i,j = 1, 2, 3 while $i \neq j$, where $\epsilon_{i,t}$ is the innovation of market i at time t, defined as the residuals estimated by the VAR. By construction, $\epsilon_{i,t}$ will have be mean 0. It is assumed that $\epsilon_{i,t}$ has a functional form (which may be normal, student-t or Generalized Error Distribution) with variance $\sigma^2_{i,t}$, in which $\sigma^2_{i,t} = \mathrm{Var}(\epsilon_{i,t} | \Omega_{t-1})$ and is the

conditional variance, where Ω_{t-1} is the information set at time t-1; $Z_{i,t}$ is the standardized innovation ($Z_{i,t} = \epsilon_{i,t}/\sigma^2_{i,t}$). Following Koutmos and Booth (1995) and Koutmos and Tucker (1996), the conditional joint distribution of the returns of the three index securities is assumed to be normal. The log likelihood function for the multivariate EGARCH model is then:

$$L(\theta) = -(1/2)(NT)\ln(2\pi) - (1/2)\sum_{t=1}^{T}(\ln|S_t| + \epsilon_t' S_t^{-1}\epsilon_t) \qquad (4.13)$$

where N is the number of equations, T is the number of observations, Θ is the 33 x 1 parameter vector to be estimated, S_t is the 3 X 3 time varying conditional variance-covariance matrix with diagonal elements given by (4.9) and cross-diagonal elements are given by (4.11); $\epsilon_t = [\epsilon_{1,t}\ \epsilon_{2,t}\ \epsilon_{3,t}]$ is the 1 X 3 vector of innovations at time t. The log likelihood function is estimated by via the Berndt, Hall, Hall and Hausman (1974) (BHHH) algorithm. To correct for heteroscedasticity, robust standard errors are estimated via RATS 4.2.

4.4.4 Extreme Value VAR (EV-VAR) Model[7]

The calculation of volatility outlined earlier may suffer from estimation problems. For example, if five-minute intervals are used, there will be at most five observations for each interval. Bear in mind that only transaction data are used. Transactions data may be affected by microstructural effects such that the real intrinsic values may not change but changes in observed prices are caused by bouncing between the bid/ask spreads. Another source of estimation biases is from infrequent trading. For example, if five

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[7] The term EV-VAR is first used in Booth et al. (1996b).

minute interval is used and there are missing data points in an interval, a biased estimate of volatility will be made no matter the missing data is "time replaced" or not.

Such estimation problems can be mitigated by using the estimation algorithm developed by Garman and Klass (1980) (GL). GL show that the variance of security returns in a period can be efficiently estimated as:

$$0.5\,(P_t^{high} - P_t^{Low})^2 - (\,2\log_e 2 - 1)\,(P_t^{Close} - P_t^{Open})^2, \tag{4.14}$$

where P_t^{High}, P_t^{Low}, P_t^{Open}, and P_t^{Close} are the natural logarithms of the high, low, opening and closing prices of the security in time period t respectively.[8] In using GL's estimator, the opening, closing, high and low prices in a given time period are needed. The main advantage of using this estimate is that it will give an efficient estimate of the intraperiod volatility as if there are hundreds of observations in that period and only the high, low, opening and closing prices are needed. In this way, the infrequent and microstructural problems outlined above can be mitigated. In the literature, Booth et al. (1996b) use GL's estimator to estimate the intraday volatilities of stock index futures in New York, London and Tokyo. Following Booth et al. (1996b), such estimate of volatility are denoted as the extreme value volatility (EV-volatility).

To explore the volatility spillover process, the following VAR is employed:

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[8] Equation (4.14) is adapted from the practical estimator $\hat{\sigma}_5^2$ in GL.

$$\begin{bmatrix} VDAX_t \\ VFDAX_t \\ VODAX_t \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{bmatrix} + \begin{bmatrix} \Phi_{11}(L) & \Phi_{12}(L) & \Phi_{13}(L) \\ \Phi_{21}(L) & \Phi_{22}(L) & \Phi_{23}(L) \\ \Phi_{31}(L) & \Phi_{32}(L) & \Phi_{33}(L) \end{bmatrix} \begin{bmatrix} VDAX_t \\ VFDAX_t \\ VODAX_t \end{bmatrix} + \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \\ \epsilon_{3t} \end{bmatrix}, \tag{4.15}$$

where $VDAX_t$, $VFDAX_t$, and $VODAX_t$ are the extreme volatilities of the DAX, the FDAX and the ODAX respectively; α_1, α_2, α_3 are constants in the EV-VAR, Φ_{ij} (L) (i,j = 1, 2, 3) are the coefficient polynomials of the VAR (e.g., $\Phi_{ij}(L) = \phi_1(L) + \phi_2(L^2) + \ldots + \phi_k(L^k)$, where k is the number of lags and L is the lag operator and ϕ_j are the coefficients), ϵ_{1t}, ϵ_{2t}, ϵ_{3t} are the error terms of the VAR. Since the variables are EV estimates of volatilities, the above VAR is labeled as the EV-VAR model.

In the EV-VAR model, if the coefficients of $\Phi_{11}(L)$ are significant but those of $\Phi_{12}(L)$ and $\Phi_{13}(L)$ are not, then there are no volatility spillovers from derivatives to the underlying index. Similar conclusions can be reached for the EV-volatilities of the FDAX and the ODAX.

To allow for the existence of heteroskedascitiy and autocorrelation in the residuals, the EV-VAR model is estimated by the Generalized Method of Moments (GMM) with k lags. Following Newey and West (1987, 1993), the heteroscedasticity and autocorrelation consistent variance-covariance matrix of the (3k+1) coefficient vector θ^j for market j (e.g., $\theta^j = (\alpha_1, \Phi_{11}(L), \Phi_{12}(L), \Phi_{13}(L)$ for j=1) , Ω^j is given by:

$$\hat{\Omega}^j = E\left[(\hat{\theta}^j - \theta^j)\ (\hat{\theta}^j - \theta^j)'\right]. \tag{4.16}$$

The robust Wald test statistic for the null hypothesis that no volatility spillover from other market to market j is:

$$(R^j \hat{\theta})' \left[R^j \hat{\Omega} (R^j)'\right]^{-1} (R^j \hat{\theta}), \tag{4.17}$$

where R^j is the 2k x (3k+1) restriction matrix. For example, with k=1 and j=DAX, R^j for no spillovers from both the FDAX and ODAX markets is [0 0 1 0, 0 0 0 1]. Under this restriction, the incremental effects of the DAX volatility on the volatility of a particular security can be examined. Similarly, the restriction matrix for isolating the impacts of volatilities of the DAX and the ODAX is [0 1 0 0, 0 0 0 1]. In this way, the direct and indirect impacts of the volatilities of each DAX security can be examined.

4.4.5 Difference Between EGARCH and EV-VAR Models

Since both the EGARCH and EV-VAR models can be used to study volatility spillovers, it is tempering to include the notion of asymmetric spillovers in the EV-VAR analysis. Recall that the EGARCH model studies the asymmetric impacts of positive and negative ***innovations*** only; while the EV-VAR targets at the variances of returns. In other words, these two models though are used to study volatility spillovers, their foci are not the same. Thus, it is not appropriate to incorporate the study of asymmetric effects of volatilities in the EV-VAR model.[9]

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9 Results of the EV-VAR model can be interpreted together with those of the EGARCH model. For example, if results from the EV-VAR model show that there are volatility spillovers from security A to security B and Univariate EGARCH model indicates that there are asymmetric spillover effects for security B, then it can be inferred that there exists asymmetric spillovers from security B to security A.

4.5 Hypotheses

4.5.1 Hypotheses One

Before examining volatility spillovers among the DAX securities, it is logical to ask whether the DAX securities share a common volatility or not. Sharing a common volatility will imply the DAX securities share the same contemporaneous volatility process, assuming that the common feature follows ARCH. Testing procedures for common volatility will follow those in Engle and Kozichi (1993), Engle and Susmel (1995) and Tse and Booth (1996). The first hypothesis is stated as:

H_0: *There is a common volatility process in the DAX securities.*

H_1: *There is no common volatility process in the DAX securities.*

4.5.2 Hypothesis Two

In previous literature, there is conflicting evidence on the causality of volatilities between derivatives. This dissertation re-examines this issue by studying the volatility of the DAX, the FDAX and the ODAX together. As put forward in Chapter 3, price discovery will occur in the least cost market. Thus, more information should be embedded in the least cost market. Under Ross's (1989) information-volatility hypothesis, more information will mean higher volatility. Bear this concept in mind, intuitively the volatility of the least cost market will also lead the volatilities of other markets. Previous studies only examine the volatilities of two instruments. Conflicting evidence in the literature may then be a result of omitting the "force" in the lead-lag relationships of volatilities across derivatives. The above discussion is formalized into hypothesis two.

H_0: *Volatility of one index security does not Granger-cause that of another security*

H_1: *Volatility of one index security does Granger-cause that of another security.*

4.5.3 Hypothesis Three

If the volatility of one index security Granger-causes the volatility of the other, the next question to be addressed is whether the quantity of information (the size of innovation in one market) as well as the quality of information (the magnitude of the innovation) are important determinants in volatility spillovers across the DAX securities. Recent studies by Koutmos and Booth (1995), Booth et al. (1997) and Koutmos and Tucker (1996) study the asymmetric volatility transmissions by the EGARCH process. Extending along this line, the next hypothesis to test is whether there is asymmetric volatility transmission in the markets for the DAX securities.

H_0: *There are no asymmetric effects between good and bad news in the volatility transmission process in the DAX securities. Effects of good and bad news are the same in volatility spillovers.*

H_1: *There are asymmetric effects between good and bad news in the volatility transmission process in the DAX securities. Good and bad news in one market will have different effects on the volatilities of other securities.*

4.5.4 Hypothesis Four

The previous hypothesis aim to test if there are asymmetric effects between the quality of news. As suggested in Bollerslev, Chou and Kroner (1992), the asymmetric effects of volatility spillovers may be the result of extreme observations such as the Stock Crash in 1987. To allow for the possibility of extreme observation, this dissertation estimates the volatility spillover process under two separate time intervals.

During the period under study, i.e., January 1992 to August 1994, the extreme observation in the European economy is the voting of the Maastricht Treaty and the European Monetary System (EMS) Crisis in 1992. During the EMS crisis in 1992, British Pound (GBP) and Italian Lira (ITL) broke away from the EMS. To prevent further disorders in the currency market, the currency grid of the EMS later was changed from 2.25% to 15%. Thus, this dissertation attempts to separate the dataset into the Pre- and Post-EMS crisis periods so that the results of information processing among the DAX securities can be compared across different structural settings. This will provide a check on the robustness of the empirical results under different structural regimes.

H_0: *The volatility spillover process among the DAX securities is the same before and after the EMS crisis.*

H_1: *The volatility spillover process among the DAX securities is different after the EMS crisis.*

4.6 Empirical Results and Discussions

4.6.1 Summary Statistics

Table 4.1 presents the number of observations and missing values under alternative data collection procedures. For the DAX and the FDAX, the problem of missing values is not severe; however, the ODAX has the largest percentage of missing values due to thin trading. As expected, the 30-minute interval produces the smallest number of missing values. Nevertheless, the number of usable observations is also the smallest under the 30-minute interval. The number of observations reflects the balance between the consideration of noise and information. Based on these data collection

procedures, five minute, 15-minute and 30-minute return series are constructed and their descriptive statistics are given in Table 4.2.

From Table 4.2, several important findings can be observed. First, there exists very strong ARCH effects for all the return series, as evidenced by the large and significant Lagrange Multipler (LM) test statistics. Since the common volatility tests require individual series to possess the common feature, which is ARCH here, the significant LM statistics give the preliminary "approval" to the study of common volatility among the index securities.[10] Second, the variances of return of options tend to be larger than those of the index and futures, no matter which option series is used. Third, returns of the DAX securities are not normally distributed, as indicated by the fact that there are excessive skewness and kurtosis in the return series.

Table 4.3 presents results of stationarity tests on the intraday volatilities of the DAX securities. Panel A of Table 4.3 shows the results of the raw series, that is, missing values are not "time replaced." For the raw series, there is strong evidence that volatilities of the DAX and the FDAX are stationary. All the Augmented Dickey-Fuller (ADF) test statistics are significant at the 0.1% level. For the volatility of the ODAX, the result is not that clear. For example, volatilities of ODAX returns under the 30-minute interval are all stationary while other measures of ODAX volatilities give ambiguous results. Panel B of the same table depicts the test results when missing values are "time replaced." The volatilities of the DAX and the FDAX remain to be stationary

[10] It is also possible to have common volatility without ARCH effects. However, it is necessary to know the type of volatility.

Table 4.2

Summary Statistics of Return Under Different Data Collection Procedures

Panel A: Return of Five Minute Interval								
Security	Mean	Min	Max	Variance	Skewness	Kurtosis	LM(1)	LM(4)
DAX	-2.93E-06	-2.85E-02	8.06E-03	6.10E-07	-1.117	34.270	38.997	62.172
FDAX	-1.00E-05	-1.07E-02	6.37E-03	8.21E-07	-0.245	3.976	391.667	898.712
ODAX1	-2.00E-05	-2.66E-02	3.55E-02	5.06E-06	0.176	13.932	144.446	257.955
ODAX2	-2.00E-05	-2.77E-02	3.57E-02	4.44E-06	0.122	15.589	148.659	226.797
ODAX3	-2.00E-05	-2.19E-02	3.57E-02	4.12E-06	0.235	15.999	164.931	304.881
ODAX4	-3.44E-06	-2.23E-02	2.19E-02	1.80E-05	0.035	2.090	552.340	820.534
ODAX5	-4.29E-06	-2.32E-02	2.16E-02	1.60E-05	0.048	2.072	720.300	1000.420
ODAX6	-4.63E-07	-2.77E-02	2.45E-02	1.50E-05	0.019	2.424	690.808	952.447
Panel B: Return of Fifteeen Minute Intervals								
Security	Mean	Min	Max	Variance	Skewness	Kurtosis	LM(1)	LM(4)
DAX	2.82E-06	-7.95E-03	9.34E-03	1.88E-06	-0.116	1.873	143.781	264.317
FDX	-2.00E-05	-1.63E-02	9.61E-03	2.17E-06	-0.395	5.838	335.589	418.766
ODAX1	-5.00E-05	-1.75E-02	1.88E-02	7.98E-06	0.091	3.592	389.143	520.819
ODAX2	-5.00E-05	-1.61E-02	1.63E-02	6.15E-06	0.019	4.050	261.977	500.796
ODAX3	-5.00E-05	-1.47E-02	1.67E-02	5.23E-06	0.038	3.620	364.823	674.410
ODAX4	-4.00E-05	-2.70E-02	2.00E-02	2.50E-05	-0.088	1.113	143.781	264.317
ODAX5	-4.00E-05	-2.33E-02	2.03E-02	1.90E-05	-0.029	1.148	269.112	346.781
ODAX6	-3.00E-05	-2.11E-02	1.79E-02	1.80E-05	-0.033	1.134	317.958	383.719
Panel C: Return of Thirty Mintues Interval								
Security	Mean	Min	Max	Variance	Skewness	Kurtosis	LM(1)	LM(4)
DAX	1.40E-05	-1.24E-02	1.20E-02	3.67E-06	-0.255	2.194	25.186	43.134
FDAX	-5.00E-05	-1.78E-02	1.10E-02	8.75E-06	-0.399	4.690	74.235	91.644
ODAX1	1.70E-05	-1.83E-02	1.74E-02	8.75E-06	0.065	2.618	131.485	254.849
ODAX2	-1.00E-04	-1.53E-02	1.81E-02	9.05E-06	0.217	3.182	87.923	189.463
ODAX3	-8.00E-05	-1.86E-02	1.82E-02	7.41E-06	0.110	3.578	175.467	272.659
ODAX4	-4.34E-06	-2.27E-02	1.93E-02	2.50E-05	-0.068	0.826	86.818	99.809
ODAX5	-6.00E-05	-2.39E-02	1.99E-02	2.40E-05	0.031	1.226	56.682	69.665
ODAX6	-3.00E-05	-2.07E-02	1.82E-02	2.10E-05	-0.052	1.173	124.271	136.459

LM(p) is the Lagrangian Multiplier test for ARCH effects for order p. All the LM statistics are significant at 0.1%. The 0.1% critical value for LM(1) is 10.8276; and the 0.1% critical value for LM(4) is 18.4669.

Table 4.3

Test of Stationarity of Intraday Volatility of DAX securities

Panel A: Without Replacement						
	Data Collection Procedure					
	5 Min		15 Min		30 Min	
Security	No Trend	With Trend	No Trend	With Trend	No Trend	With Trend
DAX	-37.315***	-37.742***	-22.783***	-23.248***	-15.125***	-15.669***
FDAX	-28.107***	-28.38***	-15.32***	-15.76***	-10.253***	-10.632***
ODAX1	-4.836***	-4.626***	-7.295***	-7.298***	-5.465***	-5.511***
ODAX2	-4.095	-4.039	-8.557***	-8.561***	-5.811***	-5.85***
ODAX3	-2.833	-2.698	-6.836***	-6.761***	-4.773***	-4.807***
ODAX4	-1.688	-1.887	-2.475	-3.572	-5.025***	-6.138***
ODAX5	-3.294	-3.448	-1.836	-2.939	-4.599***	-5.969***
ODAX6	-2.05	-2.151	0.395	-0.891	-5.438***	-6.762***

Panel B: With Replacement						
	Data Collection Procedure					
	5 Min		15 Min		30 Min	
Security	No Trend	With Trend	No Trend	With Trend	No Trend	With Trend
DAX	-36.631***	-37.092***	-22.644***	-23.153***	-15.013***	-15.576***
FDAX	-31.164***	-31.781***	-15.645***	-16.146***	-10.554***	-10.968***
ODAX1	-26.795***	-26.799***	-14.554***	-14.553***	-12.372***	-12.376***
ODAX2	-24.854***	-24.865***	-13.957***	-13.954***	-11.523***	-11.531***
ODAX3	-23.596***	-23.639***	-14.018***	-14.022***	-12.003***	-12.05***
ODAX4	-24.312***	-24.754***	-12.393***	-12.807***	-9.091***	-9.485***
ODAX5	-24.413***	-24.842***	-12.575***	-12.927***	-9.18***	-9.489***
ODAX6	-24.184***	-24.536***	-13.02***	-13.365***	-9.306***	-9.607***

*** Significant at 0.1%.

Numbers in the table are the Augmented Dicky-Fuller test statistics.

while all the volatility series of ODAX returns are now unambiguously stationary. These results illustrate the biases in having missing values "time replaced."[11] The zero variances created by the "Time Replacement" procedure will change the conclusions drawn upon.

Since volatilities of the DAX and the FDAX are stationary (i.e., I(0)), there will not be any cointegration relationships among the volatilities of the DAX securities.[12] Consequently, the VAR specified in (4.1) can be used without adding the Error Correction terms, no matter whether missing values are "time replaced" or not. Results of the bivariate Granger Causality tests are discussed in the next section.

4.6.2 Results of Bivariate Granger Causality

Table 4.4 shows the results of pair-wise Granger causality tests of the volatilities of the three DAX securities. Results vary under different methods of handling missing values. For example, when missing values are not "time replaced," volatility of ODAX1 does not Granger-cause that of the FDAX; however contrary results are obtained if missing values are "time replaced." Several important findings can be obtained from this table.

First, consider the case between the DAX and the FDAX. There is strong evidence that volatilities of the FDAX and the DAX Granger-cause each other. In other words, there is contemporaneous causality relationship (contemporaneous spillovers)

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11 Maynes and Rumsey (1993) also document similar biases induced by thinly traded stocks and missing values in event studies.

12 Cointegration requires all the series to be integrated processes of the same order.

Table 4.4

Results of Bivariate Granger Causality of Volatilities Between Index Securities

Panel A: No Replacement of Missing Values			
	Chi-Square Statistics		
Hypotheses	5-Min	15-Min	30-Min
FDAX does not Granger-cause DAX	36.525***	51.371***	37.281***
ODAX1 does not Granger-cause DAX	9.883	15.023**	6.667
ODAX2 does not Granger-cause DAX	8.969	14.138**	6.083
ODAX3 does not Granger-cause DAX	9.418	15.122**	7.027
ODAX4 does not Granger-cause DAX	8.220	1.174	23.104***
ODAX5 does not Granger-cause DAX	6.514	1.113	24.827***
ODAX6 does not Granger-cause DAX	5.440	0.682	19.983***
DAX does not Granger-cause FDAX	19.443*	128.080***	3.859
ODAX1 does not Granger-cause FDAX	7.067	5.684	5.650
ODAX2 does not Granger-cause FDAX	7.225	2.813	3.639
ODAX3 does not Granger-cause FDAX	3.453	3.740	5.690
ODAX4 does not Granger-cause FDAX	4.970	6.079	19.571***
ODAX5 does not Granger-cause FDAX	9.284	4.269	21.511***
ODAX6 does not Granger-cause FDAX	4.608	4.675	24.844***
DAX does not Granger-cause ODAX1	25.121***	7.460	2.045
DAX does not Granger-cause ODAX2	6.751	4.863	1.917
DAX does not Granger-cause ODAX3	641.056***	202.723***	160.612***
DAX does not Granger-cause ODAX4	2818.770***	1842.456***	353.354***
DAX does not Granger-cause ODAX5	1977.886***	1787.371***	256.368***
DAX does not Granger-cause ODAX6	9.584	2.009	1.642
FDAX does not Granger-cause ODAX1	9.417	10.533	6.957
FDAX does not Granger-cause ODAX2	1124.358***	148.396***	56.981***
FDAX does not Granger-cause ODAX3	639.525***	199.083***	164.566***
FDAX does not Granger-cause ODAX4	3729.821***	1875.501***	360.554***
FDAX does not Granger-cause ODAX5	11.255	26.557***	5.377
FDAX does not Granger-cause ODAX6	10.557	11.687*	2.587

(table cont'd.)

Panel B: With Replacement of Missing Values			
	Chi-Square Statistics		
Hypotheses	5-Min	15-Min	30-Min
FDAX does not Granger-cause DAX	89.644***	62.215***	35.668***
ODAX1 does not Granger-cause DAX	16.378	8.458	12.933**
ODAX2 does not Granger-cause DAX	21.062**	13.331*	15.163***
ODAX3 does not Granger-cause DAX	19.298*	8.623	10.874**
ODAX4 does not Granger-cause DAX	15.038	8.884	14.115***
ODAX5 does not Granger-cause DAX	17.690	8.696	15.303***
ODAX6 does not Granger-cause DAX	15.948	6.227	12.071**
DAX does not Granger-cause FDAX	31.243***	141.382***	3.876
ODAX1 does not Granger-cause FDAX	30.790***	20.474***	11.076**
ODAX2 does not Granger-cause FDAX	32.398***	17.023**	13.445**
ODAX3 does not Granger-cause FDAX	36.629***	24.978***	11.118**
ODAX4 does not Granger-cause FDAX	28.306***	19.756***	11.056**
ODAX5 does not Granger-cause FDAX	35.195***	14.529*	11.710**
ODAX6 does not Granger-cause FDAX	30.308***	10.555	6.260
DAX does not Granger-cause ODAX1	11.761	22.787***	4.660
DAX does not Granger-cause ODAX2	7.094	22.457***	3.108
DAX does not Granger-cause ODAX3	7.110	29.481***	3.824
DAX does not Granger-cause ODAX4	60.036***	13.290*	0.938
DAX does not Granger-cause ODAX5	61.526***	10.331*	1.351
DAX does not Granger-cause ODAX6	9.718	15.705**	0.867
FDAX does not Granger-cause ODAX1	90.925***	38.531***	24.615***
FDAX does not Granger-cause ODAX2	104.931***	34.395***	19.677***
FDAX does not Granger-cause ODAX3	98.712***	30.532***	10.095
FDAX does not Granger-cause ODAX4	97.595***	72.130***	105.976***
FDAX does not Granger-cause ODAX5	58.122***	76.398***	109.935***
FDAX does not Granger-cause ODAX6	48.131***	73.417***	97.731***

* Significant at 1%, ** Significant at 0.5%, *** Significant at 0.1%.

5-Min refers to the five minute interval procedure and so on.

between the volatilities of the FDAX and the DAX. However, test results also show that the FDAX is dominant in the causality relationship. The χ^2 test statistics for testing the null hypothesis that volatility of FDAX does not Granger-cause that of the DAX are all significant, no matter which time interval is used and how missing values are handled. On the contrary, volatility of the DAX does not Granger-cause that of the FDAX for the 30-minute return volatility. This means that only short term and medium term volatilities of the DAX affect those of the FDAX; but this causality relationship in volatility diminishes over a longer time period. This finding implies that volatility of the FDAX can be used to forecast that of the DAX over a longer time span but not the other way. From the framework of Ross (1989), the FDAX is more efficient in terms of information processing. This finding is also consistent with those in price discovery in Chapter 3.

The second pair to be considered is between the volatilities of FDAX and ODAX. Results from the "Non Replacement" and the "Time Replacement" procedures show that volatility of the FDAX Granger-causes that of the ODAX. The majority of the test statistics under the "Non-Replacement" approach and all the test statistics under the "Time Replacement" approach are significant, indicating that volatility of the FDAX Granger-causes that of the ODAX. However, ambiguous results are obtained for testing whether volatility of the ODAX Granger-causes that of the FDAX. For the "Non-Replacement" procedure, it is not clear whether a causality relationship exists since the causality test results are sensitive to the choice of implied volatilities. On the other hand, there is a bi-directional causality relationship between the volatility of the ODAX and the volatility of the FDAX under the "Time Replacement" procedure. The differences and

ambiguities in test results are partly due to the existence of missing values, particularly in short time volatilities in which the problem of missing values in the ODAX is more severe.

The third pair to be considered is the DAX and the ODAX. Again, ambiguous results arise. For example, volatility of 15-minute call ODAX return Granger-causes that of the DAX under the "Non-Replacement" method but there is no causality relationship when the "Time Replacement" approach is used. All the results show that results involving volatilities of the ODAX is sensitive to the method of handling missing values and the estimates of implied volatilities. Since the results are ambiguous, no further conclusive remarks concerning volatilities of the ODAX can be reached.

Based on the pair-wise Granger causality test results, the following conclusions are drawn: (I) there is concrete evidence that volatilities of the DAX and the FDAX Granger-cause each other, hence contemporaneous volatility spillovers between these two securities; (ii) volatility of the FDAX Granger-causes that of the ODAX, which implies that information flows from the futures market to the options market; (iii) no definite answers can be made for the volatilities of the ODAX due to problem in missing values.[13]

4.6.3 Results of Common Volatility Tests

Tables 4.5 and Table 4.6, respectively, show the results of the Univariate ARCH (UARCH) and the multivariate ARCH (MARCH) tests for common volatility among the

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[13] To remedy for ambiguities in results caused by missing values, the EV-volatility estimates (to be discussed in later sections) are used.

Table 4.5

Results of Testing for Common Volatility: Univariate ARCH Tests

Panel A: Call ODAX - Past 15 Minutes

	Test Statistics = TR^2			Weight					
				5 Min		15 Min		30 Min	
Lags	5 Min	15 Min	30 Min	w_1	w_2	w_1	w_2	w_1	w_2
1	64.67***	21.81***	12.04**	-11.35	-0.20	-3.07	0.21	-0.35	-0.09
2	549.51***	188.18***	20.84***	-0.49	-2.16	-0.05	-0.16	-0.47	0.13
4	917.68***	222.28***	14.44	4.35	0.46	-0.12	0.07	-0.58	0.08
8	1052.52***	256.26***	-	-12.55	0.15	11.45	1.88	-	-
16	953.32***	-	-	-9.55	0.08	-	-	-	-

Panel B: Call ODAX - Past Hour

	Test Statistics = TR^2			Weight					
				5 Min		15 Min		30 Min	
Lags	5 Min	15 Min	30 Min	w_1	w_2	w_1	w_2	w_1	w_2
1	58.63***	26.37***	9.50*	-4.65	-0.21	-3.01	-0.04	-0.42	-0.09
2	606.42***	184.02***	19.60**	-6.14	-1.89	-0.09	-0.16	-0.50	0.12
4	895.17***	225.44***	22.06	6.30	1.10	-0.16	-0.03	0.14	0.12
8	1047.27***	198.77***	-	-9.45	-0.41	-0.24	-0.22	-	-
16	948.18**	-	-	-6.17	-0.27	-	-	-	-

Panel C: Call ODAX - Past Day

	Test Statistics = TR^2			Weight					
				5 Min		15 Min		30 Min	
Lags	5 Min	15 Min	30 Min	w_1	w_2	w_1	w_2	w_1	w_2
1	58.98***	26.14***	7.14	-4.65	-0.20	-3.00	-0.03	-0.39	-0.05
2	697.40***	186.94***	20.89***	5.65	0.75	-0.11	-0.15	-0.47	0.16
4	935.96***	218.05***	15.92	3.86	0.40	-0.18	-0.07	-0.53	-0.08
8	1046.52***	167.05***	-	-12.25	-0.04	-0.28	-0.27	-	-
16	949.99***	-	-	-10.55	0.13	-	-	-	-

(table cont'd.)

Panel D: Put ODAX - Past 15 Minutes										
				Weight						
	Test Statistics = TR^2			5 Min		15 Min		30 Min		
Lags	5 Min	15 Min	30 Min	w_1	w_2	w_1	w_2	w_1	w_2	
1	45.15***	32.49***	6.20	-15.65	0.40	-3.67	-0.10	-0.50	0.10	
2	324.92***	165.88***	20.41***	5.65	0.69	-0.08	-0.10	-0.39	0.09	
4	776.29***	171.37***	12.27	5.65	1.15	-0.17	-0.11	0.02	-0.16	
8	883.92***	236.41***	-	5.35	-0.85	-14.60	-2.01	-	-	
16	786.87***	-	-	-1.95	-0.65	-	-	-	-	

Panel E: Put ODAX - Past Hour									
				Weight					
	Test Statistics = TR^2			5 Min		15 Min		30 Min	
Lags	5 Min	15 Min	30 Min	w_1	w_2	w_1	w_2	w_1	w_2
1	45.41***	58.68***	6.15	-15.65	0.40	-6.00	-0.06	-0.43	0.12
2	345.89***	144.70***	21.49***	5.65	0.53	-0.09	-0.15	-0.37	0.04
4	826.51***	158.06***	14.92	3.95	-0.18	-0.17	-0.14	-0.15	-0.09
8	929.58***	245.01***	-	3.45	-0.56	1.03	0.88	-	-
16	880.33***	-	-	3.45	-0.55	-	-	-	-

Panel F: Put ODAX - Past Day									
				Weight					
	Test Statistics = TR^2			5 Min		15 Min		30 Min	
Lags	5 Min	15 Min	30 Min	w_1	w_2	w_1	w_2	w_1	w_2
1	47.76***	19.00***	4.24	-13.65	0.22	-2.48	-0.25	-0.60	0.14
2	346.99***	167.77***	19.73***	5.55	0.52	-0.13	-0.11	-0.43	0.12
4	808.94***	171.20***	15.68	2.53	-0.24	-0.20	-0.13	-0.46	-0.06
8	893.01***	228.93***	-	5.35	-0.81	-4.00	-0.88	-	-
16	841.89***	-	-	5.35	-0.83	-	-	-	-

*** Significant at 0.1%, ** Significant at 0.5%, * Significant at 1%.

A negative weight means that the security is in short position. w_1 refers to be the weight of FDAX while w_2 refers to be the weight of ODAX in the portfolio. The weight of the DAX is normalized to be 1.

Table 4.6

Results of Testing for Common Volatility: Multivariate ARCH Tests

Panel A: Call ODAX - Past 15 Minutes

	Test Statistics = TR^2			Weight					
				5 Min		15 Min		30 Min	
Lags	5 Min	15 Min	30 Min	w_1	w_2	w_1	w_2	w_1	w_2
1	65.79***	29.42***	21.94***	-23.35	-0.64	-3.43	-0.03	-0.02	-0.03
2	661.59***	239.29***	44.20***	-0.77	-1.26	0.22	-0.08	-0.03	-0.11
4	1047.79***	258.35***	27.63	16.50	3.12	0.14	0.14	0.27	0.05
8	1178.81***	317.60***	-	-7.24	0.03	0.30	0.10	-	-
16	1172.61***	-	-	-6.65	0.14	-	-	-	-

Panel B: Call ODAX - Past Hour

	Test Statistics = TR^2			Weight					
				5 Min		15 Min		30 Min	
Lags	5 Min	15 Min	30 Min	w_1	w_2	w_1	w_2	w_1	w_2
1	65.79***	34.66***	42.77***	-23.25	-0.64	-2.68	-0.11	0.62	-0.02
2	658.99***	252.85***	53.32***	-5.55	-1.55	0.17	-0.04	0.02	-0.04
4	1018.31***	274.12***	27.78	-19.65	-4.16	0.17	0.05	0.32	0.06
8	1160.20***	307.13***	-	-5.67	-0.35	0.36	-0.01	-	-
16	1238.39***	-	-	10.75	-0.85	-	-	-	-

Panel C: Call ODAX - Past Day

	Test Statistics = TR^2			Weight					
				5 Min		15 Min		30 Min	
Lags	5 Min	15 Min	30 Min	w_1	w_2	w_1	w_2	w_1	w_2
1	66.86***	43.95***	20.22**	-23.35	-0.63	-2.85	0.08	-0.12	-0.08
2	715.62***	251.85***	39.67***	-12.55	-2.95	0.17	-0.01	-0.04	-0.05
4	1065.15***	261.51***	25.64	14.80	1.99	0.16	0.14	0.20	-0.06
8	1171.80***	324.25**	-	-7.19	-0.07	0.37	-0.09	-	-
16	1165.29***	-	-	-7.65	0.19	-	-	-	-

(table cont'd)

Panel D: Put ODAX - Past 15 Minutes

	Test Statistics = TR^2			Weight					
				5 Min		15 Min		30 Min	
Lags	5 Min	15 Min	30 Min	w_1	w_2	w_1	w_2	w_1	w_2
1	63.41***	53.18***	15.10*	-39.65	0.28	3.60	0.33	-0.12	-0.08
2	330.82***	199.77***	35.55***	14.95	1.99	0.13	-0.10	-0.06	-0.06
4	787.78***	228.43***	18.63	-5.15	-1.20	0.13	-0.13	0.23	-0.20
8	999.20***	296.39***	-	-2.99	-0.89	0.79	0.42	-	-
16	896.50***	-	-	-1.65	-0.65	-	-	-	-

Panel E: Put ODAX - Past Hour

	Test Statistics = TR^2			Weight					
				5 Min		15 Min		30 Min	
Lags	5 Min	15 Min	30 Min	w_1	w_2	w_1	w_2	w_1	w_2
1	62.45***	78.98***	22.38***	-31.65	0.32	2.59	0.27	-0.12	-0.11
2	361.42***	179.39***	35.71***	5.65	0.62	0.06	-0.17	-0.02	-0.11
4	899.44***	212.87***	26.10	-12.49	-2.11	0.06	-0.16	0.25	-0.18
8	1192.27***	276.39***	-	-4.35	-0.88	1.14	0.77	-	-
16	1148.37***	-	-	-2.75	-0.68	-	-	-	-

Panel F: Put ODAX - Past Day

	Test Statistics = TR^2			Weight					
				5 Min		15 Min		30 Min	
Lags	5 Min	15 Min	30 Min	w_1	w_2	w_1	w_2	w_1	w_2
1	63.76***	28.23***	21.39***	-31.65	0.12	-3.20	-0.15	0.03	-0.15
2	382.40***	205.45***	37.82***	5.65	0.65	0.03	-0.12	0.06	-0.14
4	892.62***	232.77***	30.07	-12.30	-1.99	0.02	-0.13	0.32	-0.18
8	1161.05***	285.83***	-	-4.35	-0.88	1.67	0.99	-	-
16	1090.27***	-	-	-2.75	-0.71	-	-	-	-

*** Significant at 0.1%, ** Significant at 0.5%, * Significant at 1%

A negative weight means that the security is in short position. w_1 refers to be the weight of FDAX while w_2 refers to be the weight of ODAX in the portfolio. The weight of the DAX is normalized to be 1.

index securities. The MARCH tests aims to take into account possible contemporaneous correlations (i.e., interaction effects) among the variables. Apart from the LM test statistics, the corresponding weights of FDAX (w_1) and ODAX (w_2) in the portfolio are also given. Negative numbers for w_1 and w_2 indicate that the corresponding asset is in short position.

For both the UARCH and MARCH tests, they reject overwhelmingly the null hypothesis of having a common volatility process among the index securities for the five and 15 minute returns. Note that the test statistics are significant at any conventional levels, and the results are robust for different lags and under different measures of implied volatilities. For the 30-minute return series, common volatility is found for both the UARCH and MARCH tests with four lags. That means, the three index securities do not share the same contemporaneous volatility process, assuming the common feature follows ARCH, over shorter time spans but a common volatility process exists when a longer time span is considered.

Finding no common volatility among domestic index securities is somehow counter intuitive since Engle and Susmel (1993) and Booth et al. (1996a) find common volatilities among securities in different national markets. Nevertheless, this finding is consistent with Arshanapalli and Doukas (1994), in which they also find no short term intraday common volatility for five minute return series between the S&P 500 index and the S&P 500 index futures, a pair of domestic index securities.

The finding of no short term intraday common volatilities means that each market has it own volatility process, at least on short term intraday basis.[14] From the viewpoint of volatility as a proxy for information (Ross (1989)), it implies that each market has its own short term information processing mechanism. The important implication of the findings here is that though each market is inter-related through the underlying asset, they differ in their abilities in information processing. In this way, finding no common volatility strengthens the motivation of investigating which market is more efficient in information processing.

Another interesting observation is that the UARCH and MARCH test statistics tend to be smaller for larger time intervals, and a common volatility process is found when the 30-minute return is used. Recall that Engle and Susmel (1993), Engle and Kozichi (1993) and Booth et al. (1996a) use daily or weekly data in their common volatility studies. As indicated earlier, the use of daily data ignore intraday changes in volatilities. Their conclusions may reflect the fact that markets share a common volatility process over a longer time span (which is daily or weekly basis in this instance), but not in a short time interval. Results in Arshanapalli and Doukas (1994) and in this study show that markets have different behaviors in short term volatilities. Together with previous studies in common volatility in the literature, results here imply that the index securities differ in their abilities in short term intraday information processing; however, they tend to have similar behaviors in information processing over a longer time span.

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[14] It may also argue that finding no common volatility is a result of the large amount of noise in short term intraday intervals.

This gives support to the notion that index securities have different intraday information processing abilities, hence using daily data in previous studies may ignore this useful piece of information.

4.6.4 Results from Benchmark EGARCH Model

The discussion so far suggests that the index securities do not share a common volatility process. Bivariate Granger causality test in section 4.6.2 do not give conclusive results. To have a better understanding of the intraday behavior of volatility of individual securities, the benchmark AR(1)-EGARCH(1,1) in (4.9) to (4.12), or simply the benchmark EGARCH, model is used. The benchmark EGARCH model restricts the covariance between returns among the markets (ρ_{ij} in (4.12)) to be zero. In this way, the multivariate EGARCH model is broken down into three Univariate EGARCH models. Results from the benchmark EGARCH model is presented in Table 4.7. Panel D of Table 4.7 shows the likelihood ratio test statistics under the null hypothesis that α_i, γ_i and δ_i all equal to zero. Since the likelihood ratio test statistics are highly significant; the null hypothesis of homoscedastic variance is rejected.

Results are qualitatively the same for the five, 15 and 30 minute return series and the discussion is based on the 15 minute return series. First, consider the results of the DAX returns. The coefficient γ is 0.9847 and is significant, indicating that there is very strong volatility persistence. In other words, volatility in the past period affects the volatility in the current period. Note that the sign of γ is positive, suggesting that volatility in a previous period has a positive effect on the volatility of the present period.

Table 4.7

Results from Benchmark EGARCH model

Panel A: Five Minute Interval

Security	β_0	β_1	α_0	γ	α_1	δ
	Parameter Estimates					
DAX	-3.297E-5***	0.194***	-0.144***	0.990***	6.105E-2***	-0.352***
	(4.204E-6)	(1.055E-3)	(5.476E-3)	(3.759E-4)	(7.987E-4)	(1.698E-2)
FDAX	-1.928E-5***	-0.027***	-0.143***	0.989***	9.032E-2***	-0.137***
	(5.605E-6)	(2.236E-3)	(9.486E-3)	(6.728E-4)	(2.275E-3)	(2.333E-2)
ODAX1	-5.515E-5***	-0.181***	-0.0677***	0.994***	0.049***	-0.572***
	(1.362E-5)	(0.0044)	(0.0019)	(0.0002)	(0.0008)	(0.0288)
ODAX2	-6.382E-5***	-0.194***	-0.1037***	0.991***	0.055***	-0.521***
	(1.218E-5)	(0.0041)	(0.0021)	(0.0002)	(0.0008)	(0.0244)
ODAX3	-5.849E-5***	-0.201***	-0.086***	0.993***	0.044***	-0.636***
	(1.182E-5)	(0.0039)	(0.0019)	(0.0002)	(0.0007)	(0.0288)
ODAX4	-8.493E-5**	-0.319***	-0.050***	0.995***	0.051***	-0.658***
	(2.655E-5)	(0.0061)	(0.0052)	(0.0005)	(0.0021)	(0.0690)
ODAX5	-6.699E-5**	-0.337***	-0.074***	0.993***	0.063***	-0.505***
	(2.361E-5)	(0.0056)	(0.0066)	(0.0006)	(0.0023)	(0.0543)
ODAX6	-6.675E-5**	-0.331***	-0.096***	0.991***	0.058***	-0.604***
	(2.334E-5)	(0.0048)	(0.0466)	(0.0006)	(0.0014)	(0.0466)

Panel B: Fifteen Minute Interval

Security	β_0	β_1	α_0	γ	α_1	δ
	Parameters Estimated					
DAX	-2.854E-6	0.007	-0.2002***	0.9847***	0.1128***	-0.1767***
	(1.606E-5)	(0.0044)	(0.0277)	(0.0021)	(0.0060)	(0.0419)
FDAX	-2.4862E-5	-0.0302***	-0.2310***	0.9821***	0.1544***	-0.0100***
	(1.6206E-5)	(0.0039)	(0.0264)	(0.0020)	(0.0061)	(0.0270)
ODAX1	-3.7509E-5	-0.2647***	-0.2014***	0.9828***	0.1241***	-0.2362***
	(2.9434E-5)	(0.0049)	(0.0242)	(0.0020)	(0.0066)	(0.0457)
ODAX2	-5.3223E-5	-0.1355***	-0.0971***	0.9916***	0.1047***	-0.1684***
	(2.635E-5)	(0.0059)	(0.0133)	(0.0011)	(0.0054)	(0.0479)
ODAX3	-4.2632E-5	-0.1345***	-0.1241***	0.9896***	0.1021***	-0.2088***
	(2.4921E-5)	(0.0058)	(0.0194)	(0.0016)	(0.0064)	(0.0534)
ODAX4	-3.8289E-5	-0.3957***	-0.0361***	0.9966***	0.0497***	-0.2223
	(5.4125E-5)	(0.0086)	(0.0103)	(0.0010)	(0.0056)	(0.1097)
ODAX5	-5.3522E-5	-0.2960***	-0.0605***	0.9944***	0.0603***	-0.3460**
	(5.0021E-5)	(0.0083)	(0.0131)	(0.0012)	(0.0058)	(0.1080)
ODAX6	-2.3949E-5	-0.2781***	-0.0814***	0.9925***	0.0695***	-0.2370
	(4.7948E-5)	(0.0073)	(0.0175)	(0.0016)	(0.0062)	(0.1022)

(table cont'd.)

Panel C: Thirty Minute Return Intervals						
	Parameters Estimated					
Security	β_0	β_1	α_0	γ	α_1	δ
DAX	1.9606E-5	-0.0006	-0.0431	0.9965***	0.0570***	-0.2039
	(3.454E-5)	(0.0076)	(0.0204)	(0.0016)	(0.0085)	(0.0978)
FDAX	-5.1851E-5	0.0122	-0.0485**	0.9959***	0.0588***	-0.4151***
	(3.484E-5)	(0.0063)	(0.0157)	(0.0012)	(0.0068)	(0.0797)
ODAX1	2.599E-5	-0.0852***	-0.1171***	0.9898***	0.0848***	-0.2119
	(5.077E-5)	(0.0096)	(0.0308)	(0.0026)	(0.0099)	(0.0961)
ODAX2	1.026E-4	-0.0983***	-0.1527***	0.9867***	0.0956***	-0.4262***
	(5.107E-5)	(0.0104)	(0.0314)	(0.0027)	(0.0115)	(0.0961)
ODAX3	-9.712E-5	-0.0978***	-0.1688***	0.9856***	0.1116***	-0.2757**
	(4.570E-5)	(0.0082)	(0.0418)	(0.0035)	(0.0113)	(0.0865)
ODAX4	-3.98E-7	-0.2787***	-0.0787*	0.9926***	0.0595***	-0.1455
	(8.724E-5)	(0.0128)	(0.0284)	(0.0026)	(0.0117)	(0.1618)
ODAX5	-5.558E-5	-0.2307***	-0.0502	0.9952***	0.0446***	-0.2694
	(8.671E-5)	(0.0135)	(0.0200)	(0.0019)	(0.0083)	(0.1635)
ODAX6	-2.502E-5	-0.2225***	-0.0627	0.9941***	0.0576***	-0.1431
	(8.045E-5)	(0.0118)	(0.0260)	(0.0024)	(0.0101)	(0.1455)

Panel D: LR Test and Relative Importance of Asymmetry						
	Five Minute Interval		Fifteen Minute Interval		Thirty Minute Interval	
Security	RIA	LR(3)	RIA	LR(3)	RIA	LR(3)
DAX	2.0864	2158.01***	1.4293	650.00***	1.5122	236.55***
FDAX	1.3175	3134.04***	1.2222	1019.29***	2.4191	382.14***
ODAX1	3.6769	2780.58***	1.6185	811.95***	1.5376	306.82***
ODAX2	3.1787	2697.09***	1.4051	987.69***	2.4851	378.65***
ODAX3	4.4941	2581.28***	1.5279	873.44***	1.7613	337.45***
ODAX4	4.8503	2034.02***	1.5716	521.52***	1.3405	157.38***
ODAX5	3.0400	2140.79***	2.0581	523.99***	1.7375	185.58***
ODAX6	4.0493	1973.67***	1.6212	472.72***	1.3339	173.46***

RIA denotes the relative importance of asymmetry, which is defined as $|-1+\delta|/(1+\delta)$. LR(3) is the likelihood ratio test with the restricted EGARCH model as the null.

Robust standard errors are in parentheses.

* Significant at 1%, ** Significant at 0.5 %, *** Significant at 0.1%

The asymmetric impacts of innovations can be examined through the parameter δ_js in (4.11). Asymmetry is modeled by (4.11), with partial derivatives being:

$$\partial f_i(Z_{jt}) \;/\; \partial Z_{jt} = \begin{matrix} 1 + \delta_j & for\ Z_j > 0 \\ -1 + \delta_j & for\ Z_j < 0 \end{matrix} . \tag{4.18}$$

The size effect is measured by $|Z_{j,t-1}| - E(|Z_{j,t-1}|)$ in (4.11). If δ_j is negative, a negative Z_{jt} will reinforce the size effect. Thus, negative shocks (innovations) will have greater on future volatility than a positive one. Back to the discussion, for the 15 minute DAX returns, parameter δ is negative, which means that negative innovations tend to have a greater effect than positive innovations in the variance. More specifically, the relative importance of the asymmetry (RIA) is $|-1+\delta|/(1+\delta) = 1.43$, which means that negative news increase volatility about 1.43 times more than that of positive news. Panel D of the same table shows the RIA for the benchmark EGARCH models under different data collection procedures. Results are qualitatively the same and they all show that negative innovations tend to increase volatility more than positive innovations. This finding is consistent with those documented in the literature (e.g., Koutmos and Booth (1995), Bae and Karolyi (1995) and Booth et al. (1997), etc.) that bad news tend to affect volatility more than good news. Results for the FDAX and the ODAX show similar conclusions: (I) a strong volatility persistence; and (ii) bad and good news have asymmetric effects on volatilities.

Results from the benchmark EGARCH can be interpreted together with the findings of bivariate Granger causality. Since volatilities of the DAX and the FDAX

Granger-cause each other, these results suggest that bad news (negative innovations) of the DAX (FDAX) will have a greater impact on the volatility of the FDAX (DAX) than good news (positive innovations). As the volatility of the FDAX Granger-causes that of the ODAX, bad news (negative innovations) of the FDAX will also have a greater impact on the volatility of the ODAX than good news (positive innovations).

To formally test the volatility spillover effects, the multivariate EGARCH model outlined in (4.9) to (4.12) is estimated. In spite of numerous starting values are used, the model does not converge.[15] Nevertheless, the benchmark EGARCH models provide insights to the behaviors of each individual security. More discussions and inferences can be made when results from the EV-VAR model are used.

4.6.5 EV-VAR Results

Since the use of observed volatilities cannot explain fully intraday volatility spillovers among the index securities, this section employs the extreme value volatilities to estimate the volatility spillover process. Descriptive statistics of the EV-volatilities are summarized in Table 4.8. As indicated, the EV-volatilities are not normally distributed. The Kolmogorov-Smirnov D statistics under the null of normality are all significant at 0.1%.

Table 4.9 presents the test of stationarity of the EV-volatilities. Both the ADF and Phillips-Perron (PP) test statistics show that the EV-volatilities are stationary processes for the 15 and 30 minute intervals. For the five minute EV-volatilities, the

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[15] Convergence is a well-known problem in GARCH estimation. Booth et al. (1996b) estimate a trivariate GARCH(1,1) process and have similar convergence problem in their sub-samples.

Table 4.8

Summary Statistics of Extreme Volatility

Panel A: EV of Five Minute Intervals							
Security	Mean	Median	Maximum	Minimum	Skewness	Kurtosis	D
DAX	7.008E-8	2.0E-8	0.000015	0	27.11551	1244.237	0.390176***
FDAX	1.949E-7	5.0E-8	0.000051	0	50.76146	4427.408	0.361033***
ODAX1	1.327E-6	1.3E-7	0.00152	0	13.60498	308.5763	0.384251***
ODAX2	1.257E-6	1.2E-7	0.000145	0	12.2467	271.8809	0.377799***
ODAX3	1.213E-6	1.2E-7	0.000137	0	12.92705	287.4639	0.377852***
ODAX4	5.417E-6	7.4E-7	0.000182	0	4.707251	31.33137	0.329456***
ODAX5	5.24E-6	6.7E-7	0.000158	0	4.665603	30.11329	0.331061***
ODAX6	5.001E-6	6.4E-7	0.000161	0	4.591029	29.92225	0.328336***

Panel B: EV of Fifteen Mintue Intervals							
Security	Mean	Median	Maximum	Minimum	Skewness	Kurtosis	K-S
DAX	6.342E-7	2.8E-7	0.000031	0	8.765746	137.6057	0.306348
FDAX	1.194E-6	6.8E-7	0.000133	0	29.24052	1482.848	0.309589***
ODAX1	5.318E-6	2.1E-6	0.000275	0	8.633351	128.003	0.316105***
ODAX2	5.028E-6	2.1E-6	0.000173	0	6.492577	66.6608	0.30259***
ODAX3	4.808E-6	2.1E-6	0.000178	0	7.343972	88.45692	0.299347***
ODAX4	0.00002	1.1E-5	0.000235	0	2.477527	8.639164	0.213157***
ODAX5	0.000019	1.1E-5	0.000227	0	2.455718	8.59367	0.212933***
ODAX6	0.000019	1.0E-5	0.000193	0	2.282244	7.118437	0.209157***

Panel C: EV of Thirty Minute Intervals							
Security	Mean	Median	Maximum	Minimum	Skewness	Kurtosis	K-S
DAX	1.410E-6	6.9E-7	0.00004	0	6.337048	63.93016	0.286048***
FDAX	2.179E-6	1.2E-6	0.000125	0	12.79867	299.7007	0.298156***
ODAX1	0.000011	6.2E-6	0.000242	0	5.422	44.65243	0.265467***
ODAX2	9.367E-6	5.2E-6	0.000171	0	4.805249	33.87532	0.257306***
ODAX3	8.91E-6	5.2E-6	0.000175	0	5.355789	45.35817	0.250074***
ODAX4	0.000038	2.8E-5	0.000269	0	1.972426	5.154258	0.155492***
ODAX5	0.000032	2.3E-5	0.000275	0	2.146639	6.779121	0.159759***
ODAX6	0.000031	2.2E-5	0.000262	0	1.885929	5.033171	0.153891***

*** Significant at 0.1%

D is the Kolmogorov-Smirnov test of normality.

Table 4.9

Unit Root Tests of Extreme Volatilities

Test	Security	5 Min	15 Min	30 Min
Panel A: Results of the Augmented Dickey Fuller Test				
ADF no trend	DAX	-13.719***	-8.868***	-7.558***
ADF with trend	DAX	-14.095***	-9.137***	-8.011***
ADF no trend	FDAX	-13.582***	-7.990***	-6.984***
ADF with trend	FDAX	-14.224***	-8.357***	-7.437***
ADF no trend	Call ODAX - Past 15 Minutes	-4.501***	-8.649***	-6.883***
ADF with trend	Call ODAX - Past 15 Minutes	-4.523***	-8.657***	-6.884***
ADF no trend	Call ODAX - Past Hour	-3.234***	-8.455***	-7.271***
ADF with trend	Call ODAX - Past Hour	-3.301	-8.453***	-7.269***
ADF no trend	Call ODAX - Past Day	-4.879***	-8.829***	-6.627***
ADF with trend	Call ODAX - Past Day	-4.764***	-8.835***	-6.628***
ADF no trend	Put ODAX - Past 15 Minutes	-3.505***	-5.486***	-5.173***
ADF with trend	Put ODAX - Past 15 Minutes	-3.725*	-5.815***	-5.266***
ADF no trend	Put ODAX - Past Hour	-3.495***	-5.784***	-5.603***
ADF with trend	Put ODAX - Past Hour	-3.634*	-6.018***	-5.807***
ADF no trend	Put ODAX - Past Day	-3.186***	-5.855***	-5.897***
ADF with trend	Put ODAX - Past Day	-3.681*	-6.097***	-6.129***
Panel B: Results of Philips-Perron Test				
PP no trend	DAX	-136.92***	-80.527***	-50.662***
PP with trend	DAX	-135.71***	-79.767***	-49.995***
PP no trend	FDAX	-147.54***	-82.848***	-54.926***
PP with trend	FDAX	-145.07***	-81.709***	-54.145***
PP no trend	Call ODAX - Past 15 Minutes	-150.23***	-81.411***	-42.491***
PP with trend	Call ODAX - Past 15 Minutes	-150.03***	-81.390***	-42.480***
PP no trend	Call ODAX - Past Hour	-150.63***	-81.024***	-40.204***
PP with trend	Call ODAX - Past Hour	-150.39***	-81.000***	-40.182***
PP no trend	Call ODAX - Past Day	-150.64***	-76.867***	-41.143***
PP with trend	Call ODAX - Past Day	-150.28***	-76.811***	-41.086***
PP no trend	Put ODAX - Past 15 Minutes	-157.76***	-84.819***	-53.706***
PP with trend	Put ODAX - Past 15 Minutes	-157.16***	-84.905***	-54.088***
PP no trend	Put ODAX - Past Hour	-156.76***	-81.650***	-49.888***
PP with trend	Put ODAX - Past Hour	-156.21***	-81.733***	-50.192***
PP no trend	Put ODAX - Past Day	-155.66***	-82.821***	-48.777***
PP with trend	Put ODAX - Past Day	-155.15***	-82.805***	-49.082***

*** Significant at 0.1%, * Significant at 1%.

Table 4.10

Correlation Between Observed and Extreme Volatilities

Panel A: Extreme Volatility and Observed Volatility (Time Replacement)			
	5 Minute	15 Minute	30 Minute
DAX	0.73558	0.74826	0.66074
FDAX	0.79819	0.69207	0.50864
ODAX	0.74451	0.77366	0.80563

Panel B: Extreme Volatility and Observed Volatility (Non-Replacement)			
	5 Minute	15 Minute	30 Minute
DAX	0.73772	0.76080	0.68098
FDAX	0.85069	0.73695	0.55389
ODAX	0.83186	0.84965	0.88860

Panel C: Observed Volatilities (Non-Replacement and Time Replacement)			
	5 Minute	15 Minute	30 Minute
DAX	0.99029	0.99136	0.99286
FDAX	0.91269	0.93724	0.97746
ODAX	0.82814	0.84637	0.87833

All correlation coefficients are significant at 0.1%.

ADF test statistics are significant if time trends are not included. Since volatilities are not increasing functions of time and time trend are not significant (not even at 5%), it is appropriate to use the ADF test with no time trend for the five minute EV-volatilities. Again, results of both the ADF and PP test results show that the EV-volatilities are stationary, hence there are no cointegration relationships among the EV-volatilities. Thus, the EV-VAR model posited in (4.15) can be used to test for the effects of volatility spillovers.

To test for the effects of volatility spillovers, the robust Wald statistics outlined in (4.17) are calculated. Results of the robust Wald test statistics are presented in Table 4.11. Note that the robust Wald statistics are calculated with one and four lags. The objective is to test the effect of higher lags on the spillover process. Since lag one will contain more recent information and effects of higher lags may cancel out one another, results from using one lag in the EV-VAR will provide the answer on how does volatility in last period affect that of the current period. In this essence, the rationale of using one lag in the EV-VAR model is very similar to that of the benchmark EGARCH(1,1) models.

The discussion of the EV-VAR consists of three main parts. Initially, results of spillover effect of using one lag in the EV-VAR model are discussed. Then results of using four lags are addressed. Finally, a comparison of results of using different number of lags can be made.

First, consider the results of using one lag in the EV-VAR model. From Table 4.11, there is strong evidence to reject the null hypothesis that there is no volatility

Table 4.11

Robust Wald Test Statistics for Extreme Volatility Spillovers

Panel A: Call Options Estimated by Implied Volatilities of Past 15 Minutes					
			Restricting to Effects of		
Security	Return Interval	Lags	DAX only	FDAX only	ODAX only
DAX	5 Min	1	26.24***	18.75***	25.45***
FDAX	5 Min	1	23.40***	27.98***	25.55***
ODAX	5 Min	1	85.65***	86.11***	8.77
DAX	5 Min	4	202.62***	21.75**	308.38***
FDAX	5 Min	4	59.58***	19.78	63.00***
ODAX	5 Min	4	185.65***	188.87***	24.96**
DAX	15 Min	1	56.63***	34.47***	112.29***
FDAX	15 Min	1	12.64**	21.92***	47.74***
ODAX	15 Min	1	74.31***	113.95***	27.07***
DAX	15 Min	4	58.81***	43.00***	196.35***
FDAX	15 Min	4	23.54**	27.39***	115.04***
ODAX	15 Min	4	68.14***	85.12***	11.50
DAX	30 Min	1	14.84***	20.02***	23.10***
FDAX	30 Min	1	19.24***	21.70***	44.21***
ODAX	30 Min	1	86.37***	77.21***	8.24
DAX	30 Min	4	25.58***	23.06**	125.65****
FDAX	30 Min	4	28.72***	14.89	193.15***
ODAX	30 Min	4	78.72***	61.74***	22.16**

(table cont'd.)

Panel B: Call Options Estimated by Implied Volatilities of Past Hour					
			Restricting to Effects of		
Security	Return Interval	Lags	DAX only	FDAX only	ODAX only
DAX	5 Min	1	26.42***	16.75***	25.54***
FDAX	5 Min	1	25.77***	29.74***	25.51***
ODAX	5 Min	1	110.29***	110.40***	8.01
DAX	5 Min	4	217.07***	24.65**	307.52***
FDAX	5 Min	4	78.78***	21.22	63.65***
ODAX	5 Min	4	181.50***	188.18***	16.28
DAX	15 Min	1	59.85***	38.77***	110.13***
FDAX	15 Min	1	19.17***	26.99***	47.22***
ODAX	15 Min	1	62.14***	91.98***	17.95***
DAX	15 Min	4	57.07***	49.11***	188.92***
FDAX	15 Min	4	29.24***	29.70***	107.35***
ODAX	15 Min	4	84.87***	103.11***	13.14
DAX	30 Min	1	22.31***	24.92***	22.74***
FDAX	30 Min	1	22.85***	26.20***	42.53***
ODAX	30 Min	1	88.09***	84.17***	6.18
DAX	30 Min	4	36.97***	25.14***	125.92***
FDAX	30 Min	4	38.43***	17.06	159.40***
ODAX	30 Min	4	59.11***	77.79***	11.03

(table cont'd.)

Panel C: Call Options Estimated by Implied Volatilities of Past Day					
			Restricting to Effects of		
Security	Return Interval	Lags	DAX only	FDAX only	ODAX only
DAX	5 Min	1	28.75***	18.04***	25.47***
FDAX	5 Min	1	34.75***	32.64***	25.37***
ODAX	5 Min	1	100.37***	97.09***	8.16
DAX	5 Min	4	208.25***	22.76**	303.72***
FDAX	5 Min	4	63.25***	19.43	63.64***
ODAX	5 Min	4	173.27***	171.76***	19.86
DAX	15 Min	1	57.96***	37.49***	107.34***
FDAX	15 Min	1	17.94***	28.40***	46.85***
ODAX	15 Min	1	76.89***	102.19***	15.15***
DAX	15 Min	4	59.44***	43.48***	181.25***
FDAX	15 Min	4	30.11***	29.85***	113.71***
ODAX	15 Min	4	90.56***	118.86***	5.78
DAX	30 Min	1	24.99***	23.57***	21.62***
FDAX	30 Min	1	26.88***	24.94***	37.38***
ODAX	30 Min	1	96.39***	96.88***	5.40
DAX	30 Min	4	37.24***	28.13***	84.75***
FDAX	30 Min	4	35.33***	17.50	121.58***
ODAX	30 Min	4	45.29***	46.56***	12.95

(table cont'd.)

Panel D: Put Options Estimated by Implied Volatilities of Past 15 Minutes					
Security	Return Interval	Lags	Restricting to Effects of		
			DAX only	FDAX only	ODAX only
DAX	5 Min	1	22.68***	23.43***	25.49***
FDAX	5 Min	1	28.30***	22.62***	25.23***
ODAX	5 Min	1	143.13***	145.94***	10.81**
DAX	5 Min	4	195.93***	37.40***	287.65***
FDAX	5 Min	4	58.59***	23.39**	68.11***
ODAX	5 Min	4	275.35***	283.84***	19.08
DAX	15 Min	1	60.21***	55.05***	106.05***
FDAX	15 Min	1	30.32***	27.41***	46.15***
ODAX	15 Min	1	316.55***	326.92***	26.36***
DAX	15 Min	4	64.67***	43.01***	180.15***
FDAX	15 Min	4	33.54***	28.55***	142.36***
ODAX	15 Min	4	496.36***	505.35***	31.99***
DAX	30 Min	1	9.15*	21.26***	23.87***
FDAX	30 Min	1	31.73***	15.40***	41.14***
ODAX	30 Min	1	287.58***	290.09***	14.97***
DAX	30 Min	4	23.01***	25.55***	120.20***
FDAX	30 Min	4	30.60***	8.45	149.71***
ODAX	30 Min	4	237.83***	191.07***	21.15**

(table cont'd.)

Panel E: Put Options Estimated by Implied Volatilities of Past Hour					
			Restricting to Effects of		
Security	Return Interval	Lags	DAX only	FDAX only	ODAX only
DAX	5 Min	1	22.53***	23.92***	25.41***
FDAX	5 Min	1	27.70***	21.44***	25.19***
ODAX	5 Min	1	152.63***	153.55***	10.81**
DAX	5 Min	4	199.85***	42.76***	288.16***
FDAX	5 Min	4	57.53***	23.64**	69.00***
ODAX	5 Min	4	288.02***	303.95***	12.22
DAX	15 Min	1	63.70***	54.38***	106.22***
FDAX	15 Min	1	31.47***	28.33***	45.73***
ODAX	15 Min	1	403.18***	414.89***	21.59***
DAX	15 Min	4	58.17***	44.77***	176.01***
FDAX	15 Min	4	46.97***	31.52***	145.16***
ODAX	15 Min	4	497.95***	491.58***	24.95**
DAX	30 Min	1	8.64*	19.97***	23.23***
FDAX	30 Min	1	27.90***	15.11***	35.12***
ODAX	30 Min	1	288.03***	274.31***	12.00**
DAX	30 Min	4	26.42***	24.71**	125.69***
FDAX	30 Min	4	30.95***	8.94	134.72***
ODAX	30 Min	4	276.52***	197.95***	25.40***

(table cont'd.)

Panel F: Put Options Estimated by Implied Volatilities of Past Day					
Security	Return Interval	Lags	Restricting to Effects of		
			DAX only	FDAX only	ODAX only
DAX	5 Min	1	18.96***	20.59***	25.25***
FDAX	5 Min	1	28.97***	24.03***	25.22***
ODAX	5 Min	1	174.82***	172.26***	12.11**
DAX	5 Min	4	199.96***	41.03***	283.42***
FDAX	5 Min	4	61.91***	24.71**	67.61***
ODAX	5 Min	4	347.17***	354.66***	13.64
DAX	15 Min	1	58.23***	48.62***	108.56***
FDAX	15 Min	1	27.88***	23.25***	46.23***
ODAX	15 Min	1	457.80***	437.37***	21.55***
DAX	15 Min	4	59.80***	39.88***	187.60***
FDAX	15 Min	4	40.32***	31.97***	151.04***
ODAX	15 Min	4	609.03***	559.62***	29.40***
DAX	30 Min	1	8.22	18.10***	23.85***
FDAX	30 Min	1	26.08***	14.61***	36.95***
ODAX	30 Min	1	405.07***	391.65***	8.41
DAX	30 Min	4	29.87***	23.32**	144.60***
FDAX	30 Min	4	36.66***	10.17	141.24***
ODAX	30 Min	4	310.40***	203.80***	22.83**

*** Significant at 0.1%, ** Significant at 0.5%, * Significant at 1%

The heteroscedasticity and autocorrelation consistent covariance matrices used in the calculation of the robust Wald tests are derived from Generalized Method of Moments (GMM).

spillovers from the derivatives to the index.[16] Under the null of no spillover effects from the derivatives to the index, the calculated Wald statistics are significant under different data collection procedures.[17] That means, volatilities of the FDAX and ODAX spillovers to the volatility of the DAX. Since the results are robust across different time intervals, they also imply that intraday volatility of the DAX are affected by those of the FDAX and ODAX under short and long terms. This finding is consistent with those in bivariate Granger causality tests in which the volatility of the FDAX is found to Granger-cause that of the DAX. For the FDAX, similar results are obtained. That means, volatilities from the DAX and the ODAX do affect that of the FDAX, both under short and long terms. For the ODAX, the same conclusions are reached. Volatilities of both the call and the put options are affected by the volatilities of the DAX and the FDAX. Thus, volatilities of the three markets spillover to one another. In this way, there exists both direct and indirect spillover effects among the three securities. For example, volatility of the FDAX can directly affect that of ODAX, and it can also affect the volatility of the ODAX indirectly through the DAX. Second, consider the results of using four lags in the EV-VAR model. The results are qualitatively the same as those using one lag. The input here is that past lags of volatility of another market will also affect a market's volatility in the current period. From an information processing perspective, information

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16 The effect of spillover effects from the same market (self-spillover) is not discussed since the concern is in cross markets spillovers. Nevertheless, results show that the ODAX is less affected by self-spillovers.

17 Note that 0.1% significance level is used for the EV of five minute interval; 0.5% significance level is used for the 15 minute interval and 1% is used for the 30 minute interval.

(variance) from one market will be assimilated in another market. In other words, results here imply that the three markets all contribute to the information processing mechanism. Therefore, the three markets should be treated as a whole system in the intraday information process. This volatility spillover relationship is summarized graphically in Figure 4.1. The arrows indicate the respective causality relationships.

Finally, it is worthwhile to examine the effects of increase in lags on the spillover effects. For the DAX and the FDAX, the increases of lags in the EV-VAR model lead to larger robust Wald statistics. Thus, there are more significant spillover effects from other securities to the DAX and the FDAX if more lags are employed in the EV-VAR model. This conclusion is also robust across different time intervals. In other words, past volatilities (apart that from the past period) of other securities will also affect the volatilities of the DAX and the FDAX. For the ODAX, with the exception of ODAX1, the general picture is that the spillover effects become greater when the five and 15 minute intervals are used. On the other hand, the significance of spillover effects become lower (lower Wald statistics) when the 30 minute interval is used. It indicates that under the 30 minute interval, the impacts of different lags on the spillover process start to cancel out one another. However, the spillover effect is still significant at the significance level chosen.

Given there are volatility spillovers among the index securities, it is useful to reconsider results from the benchmark EGARCH model. Results from the benchmark EGARCH model shows that there exist asymmetric effects with negative innovations having a more prominent effects on future volatilities than positive innovations. Together

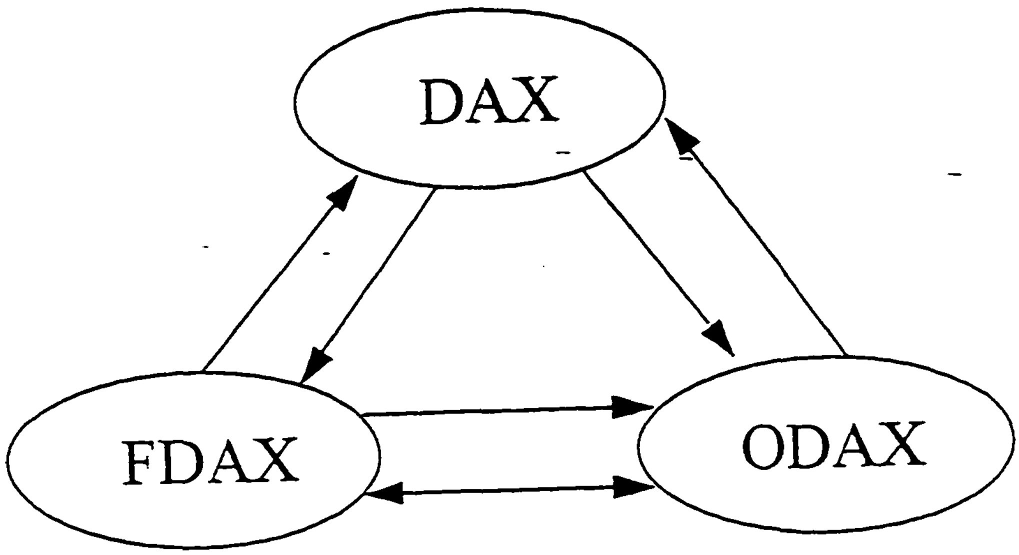

Figure 4.1

Volatility Spillovers Among the DAX Securities
Arrows denote the causal relationships.

with the finding that volatility spillovers exist in the index securities, overall results imply that there exist asymmetric spillover effects. Negative news in one market (say, the DAX) will affect the volatility of another market (say, the FDAX) more than positive news. The important implication is that the three index securities should be considered as a whole system in the information processing mechanism. This conclusion is also consistent with those in price discovery and information sharing in Chapter 3.

4.6.6 Innovation Accounting and Impulse Response Functions

To provide more insight in the speed and sources of transmissions of volatilities, VAR innovations accounting are used. The use of innovation accounting can give a better understanding to the Forecast Error Variance Decomposition (FEVD), the percentage of forecast error variance explained by self innovations and shocks in other markets. In Fleming, Ostdiek and Whaley (1996), they argue that lower trading costs in derivatives markets will posit lead-lag relationships among the index securities in which futures lead options, and options lead the spot. Consistent with their trading cost argument, a prior order of FDAX, ODAX and DAX is used in the Cholesky decomposition of the impulse response function. Since the EV-VAR residuals exhibit strong correlations (Panel A of Table 4.12), the residuals are orthogonalized.

Panel B of Table 4.12 shows the FEVD of the 15-minute volatility series. Fifteen minute interval is chosen because this interval has the highest spillover effects. Results show that most of the adjustment are finished in five periods. For the DAX, the primary source of explanation to the forecast error (FE) is itself. Over a life of five periods, FE from the DAX explains 97% of its total forecast error. The FDAX and the ODAX just

Table 4.12

Correlation Between Residuals of the EV-VAR and Accounting Innovations in Extreme Volatilities of DAX securities

Panel A: Correlation of Residuals of the EV-VAR		
	FDAX	ODAX
DAX	0.2637***	0.1215***
ODAX	0.1292***	

Panel B: Accounting Innovations in EV-Volatilities				
		By Innovations in		
Market Explained	Horizon (Periods)	FDAX	ODAX	DAX
FDAX	1	100.0000	0.0000	0.0000
	2	29.3230	0.7212	69.9558
	3	18.3908	0.8422	80.7671
	4	15.5164	0.9746	83.5091
	5	13.8610	1.0248	85.1142
	10	12.3496	1.1022	86.5482
	15	12.2359	1.1152	86.6489
	20	12.2223	1.1174	86.6603
ODAX	1	6.9527	93.0473	0.0000
	2	3.5772	23.1367	73.2861
	3	2.9403	11.8491	85.2107
	4	3.1285	11.4233	85.4483
	5	3.3616	10.7511	85.8873
	10	3.4883	8.8438	87.6679
	15	3.5081	8.5028	87.9891
	20	3.5110	8.4403	88.0487
DAX	1	1.4763	1.0151	97.5086
	2	1.5167	1.0152	97.4681
	3	1.5310	1.0149	97.4541
	4	1.5418	1.0154	97.4428
	5	1.5517	1.0170	97.4314
	10	1.5609	1.0190	97.4201
	15	1.5617	1.0194	97.4189
	20	1.5618	1.0195	97.4187

*** Significant at 0.1%.

Each entry indicates the percentage of forecast error variance of the market explained by self innovations and the other two markets. The decomposition is calculated using the order of the FDAX, the ODAX and the DAX, which reflects the trading cost hypothesis put forward by Fleming, Ostdiek and Whaley (1996).

contribute marginally to the FE of the DAX, with a contribution of 1.55% and 1.02% respectively. For the FDAX, the primary source of FE is also the DAX, though the proportion of FDAX FE is much higher. Over a life of five periods, the contribution of the FDAX is 13.86%, while the contribution of ODAX is somehow a small 1.02%. Note that the contribution of the FDAX decreases over time while that of the DAX increases. It means that in the short term, self innovations play a more important role in the FE. Over a longer time period, however, information still comes out from the cash market. For the ODAX, the FDAX contributes 3.4% to the FE, with 10.75% from itself and 85.9% from the DAX over a life of five periods. Again, the contributions of the FDAX and ODAX to FE decrease over time while that of the DAX increases.

Economically, the results show that the pricing of the derivatives rely on information about the underlying asset. Innovations in the underlying asset will then affect volatilities of the derivatives. The results suggest that over a longer time period, the main source of FE, hence information, is still the underlying asset. The results are intuitive appealing since the underlying index has infrequent trading problem and the high liquidity in the derivatives markets can take up the information effect in a short time period. But over a longer time horizon, the underlying asset is still the major source of information.

Table 4.13 shows the normalized individual and cumulative impulse response function of the index securities to a unit shock (a standard deviation) in self and other markets. Figures 4.2 to 4.4 depict the impulse response function graphically. Results show that the FDAX reacts strongly to its own shocks and shocks in the DAX. The

Table 4.13

Individual Impulse Response to a Unit Shock in One Market

Origin of Shock	k th period	Impulse Response In		
		FDAX	ODAX	DAX
FDAX	1	0.5079	0.0606	1.0401
	2	0.1620	0.0691	0.2017
	3	0.1320	0.0953	0.1794
	4	0.1366	0.0559	0.1362
	5	0.1144	0.0678	0.1147
	5 (cumulative)	1.0528	0.3488	1.6722
	10 (cumulative)	1.2995	0.5779	1.9157
	15 (cumulative)	1.3773	0.6872	1.9879
	20 (cumulative)	1.4051	0.7343	2.0129
ODAX	1	0.0000	0.2218	0.8625
	2	0.0836	0.0739	0.0868
	3	0.0826	0.1264	0.1188
	4	0.0794	0.0690	0.0847
	5	0.0673	0.0732	0.0703
	5 (cumulative)	0.3129	0.5644	1.2231
	10 (cumulative)	0.4832	0.7908	1.3839
	15 (cumulative)	0.5432	0.8899	1.4383
	20 (cumulative)	0.5661	0.9313	1.4587
DAX	1	0.0000	0.0000	8.4530
	2	0.8235	0.4162	0.8270
	3	0.8042	0.5788	1.1674
	4	0.6318	0.2367	0.8064
	5	0.5686	0.2849	0.5892
	5 (cumulative)	2.8280	1.5166	11.8431
	10 (cumulative)	4.1358	2.6406	13.1431
	15 (cumulative)	4.5345	3.1808	13.5155
	20 (cumulative)	4.6749	3.4152	13.6424

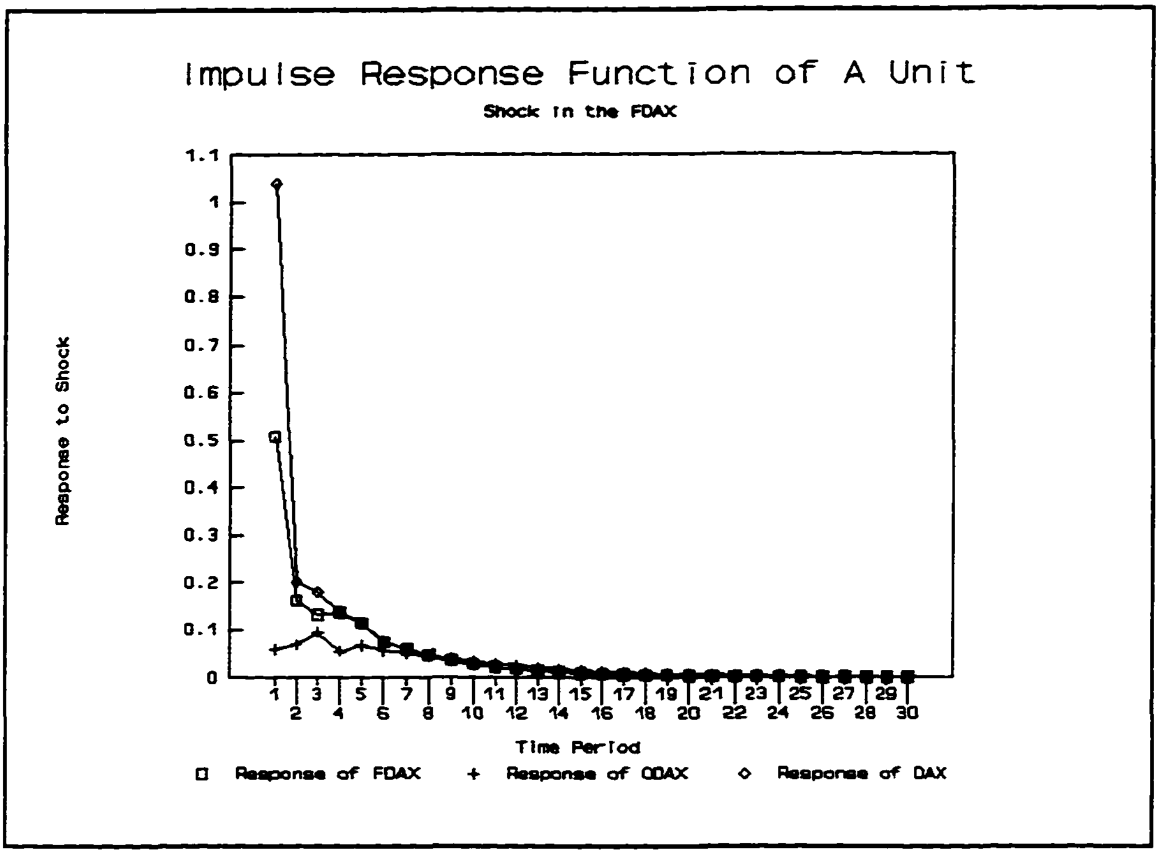

Figure 4.2

Impulse Response Function of DAX Securities to a Unit Shock in the FDAX

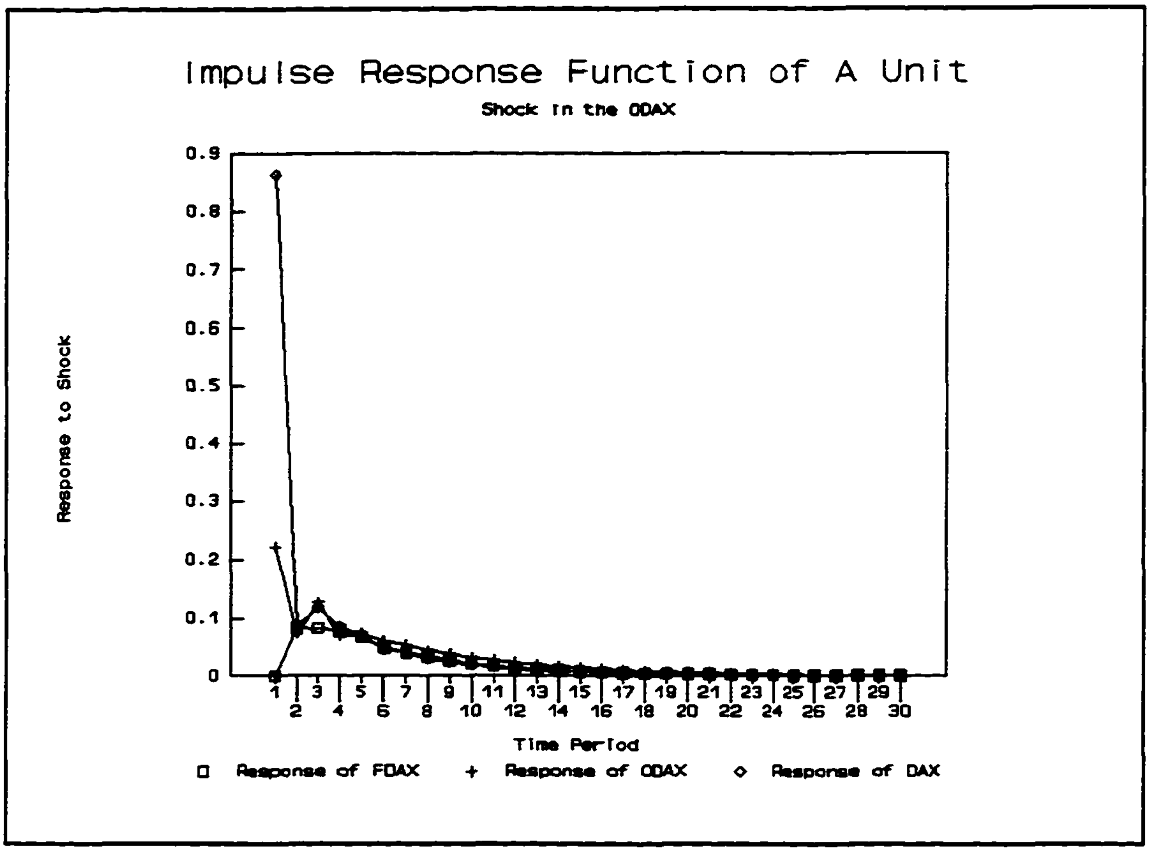

Figure 4.3

Impulse Response Function of DAX Securities to a Unit Shock in the ODAX

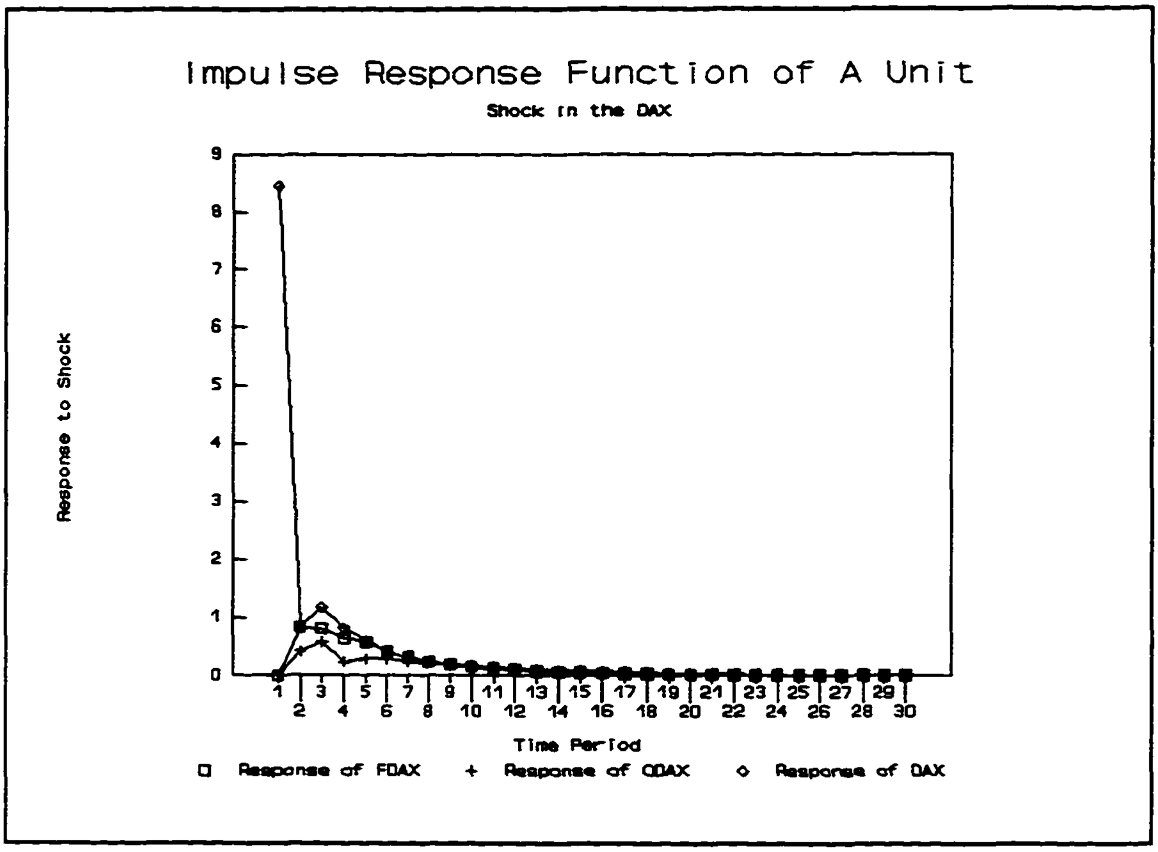

Figure 4.4

Impulse Response Function of DAX Securities to a Unit Shock in the DAX

reaction to shocks in the DAX is the strongest, while the reaction to shock in the ODAX is not that strong. The ODAX reacts strongly to shocks in the DAX, and has similar reactions to its own shocks and those of the FDAX. Finally, reactions of the DAX to self innovations are much stronger than those of the FDAX and the ODAX.

4.6.7 Pre and Post EMS Crisis Volatility Spillovers

To test for effects of the EMS Crisis on the volatility spillover process, the full sample is divided into the pre- and post EMS subsamples.[18] The Pre-EMS Crisis is from January 1992 to August 1992 while the Post-EMS Crisis is from October 1992 to March 1994. The month September 1992 is left out since it is the height of the EMS Crisis with the GBP and ITL under tremendous selling pressure. In September 1992, the GBP and the ITL finally left the EMS. Table 4.14 presents the volatility spillover results for the pre- and post-EMS Crisis subsamples. Graphically, the spillover relationships are depicted in Figure 4.5 to Figure 4.7. Similar to Figure 4.4, the arrows represent the respective causal relationships.

For the DAX volatility, there is evidence that the spillover effects become stronger after the EMS crisis. The majority of the Wald statistics of the post-EMS crisis are more significant than those of the pre-EMS crisis. For the FDAX volatility, there is a decrease in volatility spillover effects from the ODAX to the FDAX. The Wald statistics in the post-EMS crisis period are generally smaller. However, the spillover

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[18] The multivariate EGARCH model is also estimated for both the pre and post-EMS Crisis subsamples. However, the EGARCH model does not converge under either subsample. Thus, only the EV-VAR model is used here for ease of comparison with the results of using the full sample.

Table 4.14

Test of Volatility Spillovers Before and After the EMS Crisis

Panel A: Call Options Estimated by Implied Volatilities of Past 15 Minutes

			Restricting to Effects of					
	Return		DAX Only		FDAX Only		ODAX Only	
Security	Interval	Lags	Before	After	Before	After	Before	After
DAX	5 Min	1	5.29	29.47***	4.27	17.84***	57.18***	21.11***
FDAX	5 Min	1	26.50***	25.23***	12.94**	32.10***	55.25***	19.56***
ODAX	5 Min	1	16.32***	76.75***	14.58***	75.85***	9.84	6.52
DAX	5 Min	4	17.37	307.04***	4.71	16.23	76.38***	405.30***
FDAX	5 Min	4	31.95***	56.89***	13.33	19.58*	134.35***	47.06***
ODAX	5 Min	4	42.65***	126.55***	39.85***	125.36***	6.39	25.41***
DAX	15 Min	1	38.46***	177.37***	11.02**	27.12***	84.73***	174.48***
FDAX	15 Min	1	66.61***	12.56**	3.96	26.18***	104.81***	56.02***
ODAX	15 Min	1	48.21***	35.60***	20.90***	72.63***	6.48	25.26***
DAX	15 Min	4	19.69	80.05***	9.60	50.14***	96.14***	206.56***
FDAX	15 Min	4	35.54***	21.50	7.01	27.19***	158.65***	68.76***
ODAX	15 Min	4	56.34***	73.76***	20.84	100.09***	6.57	18.54
DAX	30 Min	1	21.00***	11.63**	9.22	23.66***	43.29***	25.21***
FDAX	30 Min	1	15.87***	11.83**	7.07	17.87***	35.88***	79.18***
ODAX	30 Min	1	14.92***	65.20***	12.08**	81.93***	1.79	14.40***
DAX	30 Min	4	14.68	39.10***	14.44	19.29	25.69***	149.96***
FDAX	30 Min	4	14.54	31.24***	10.08	6.52	43.25***	205.81***
ODAX	30 Min	4	32.59***	41.76***	28.53***	37.60***	7.10	20.14

(table cont'd.)

Panel B: Call Options Estimated by Implied Volatilities of Past Hour

Security	Return Interval	Lags	Restricting to Effects of: DAX Only Before	DAX Only After	FDAX Only Before	FDAX Only After	ODAX Only Before	ODAX Only After
DAX	5 Min	1	7.98	27.57***	3.94	15.20***	57.56***	21.27***
FDAX	5 Min	1	30.93***	24.15***	12.49**	29.23***	53.61***	19.58***
ODAX	5 Min	1	26.22***	82.50***	27.08***	80.42***	8.43	5.98
DAX	5 Min	4	17.83	303.99***	6.44	16.19	79.71***	400.59***
FDAX	5 Min	4	32.30***	69.96***	14.05	18.88	124.74***	48.15***
ODAX	5 Min	4	51.06***	124.52***	56.53***	123.45***	7.91	13.26
DAX	15 Min	1	43.80***	175.42***	13.71***	27.07***	84.74***	173.32***
FDAX	15 Min	1	71.00***	16.94***	7.70	26.75***	105.17***	56.78***
ODAX	15 Min	1	56.40***	37.96***	21.36***	67.83***	6.70	16.74***
DAX	15 Min	4	21.62	83.10***	11.34	44.16***	85.25***	201.81***
FDAX	15 Min	4	39.47***	18.46	9.71	25.44***	142.99***	54.32***
ODAX	15 Min	4	47.58***	74.51***	18.64	108.76***	10.24	13.92
DAX	30 Min	1	26.92***	17.69***	16.26***	24.38***	35.36***	24.63***
FDAX	30 Min	1	20.93***	13.73***	10.64**	20.72***	33.44***	55.02***
ODAX	30 Min	1	24.30***	59.60***	16.22***	73.95***	1.74	9.00*
DAX	30 Min	4	13.00	50.62***	13.20	19.15	21.56*	138.32***
FDAX	30 Min	4	19.03*	34.17***	16.55	5.79	34.76***	146.82***
ODAX	30 Min	4	20.34*	31.29***	36.38***	45.56***	15.65	7.81

(table cont'd.)

Panel C: Call Options Estimated by Implied Volatilities of Past Day								
			Restricting to Effects of					
			DAX Only		FDAX Only		ODAX Only	
Security	Return Interval	Lags	Before	After	Before	After	Before	After
DAX	5 Min	1	7.41	30.02***	4.06	16.79***	57.70***	21.25***
FDAX	5 Min	1	28.81***	33.51***	10.98**	33.99***	54.79***	19.46***
ODAX	5 Min	1	23.33***	87.06***	19.96***	84.31***	8.25	6.23
DAX	5 Min	4	18.36	296.51***	5.66	19.91*	79.09***	397.73***
FDAX	5 Min	4	34.94***	59.59***	15.73	18.73	134.52***	48.06***
ODAX	5 Min	4	65.79***	125.80***	67.34***	115.63***	11.06	16.27
DAX	15 Min	1	40.68***	168.93***	11.04**	31.68***	85.71***	165.44***
FDAX	15 Min	1	69.15***	16.85***	4.89	31.92***	106.56***	57.04***
ODAX	15 Min	1	57.62***	45.73***	24.02***	77.92***	5.55	13.43***
DAX	15 Min	4	20.24	80.96***	9.03	42.11***	99.23***	184.10***
FDAX	15 Min	4	38.01***	26.84***	7.42	27.06***	152.90***	76.12***
ODAX	15 Min	4	63.63***	84.06***	31.07***	112.87***	7.94	5.01
DAX	30 Min	1	23.47***	21.18***	11.38**	23.75***	34.63***	24.34***
FDAX	30 Min	1	18.41***	15.62***	8.66	18.15***	29.40***	56.92***
ODAX	30 Min	1	19.73***	82.88***	10.66**	95.46***	1.14	3.60
DAX	30 Min	4	12.60	39.52***	14.29	18.74	20.15*	104.90***
FDAX	30 Min	4	19.43*	24.30**	19.82*	5.79	33.75***	112.71***
ODAX	30 Min	4	30.60***	38.35***	68.92***	52.17***	20.74*	10.14

(table cont'd.)

Panel D: Put Options Estimated by Implied Volatilities of Past 15 Minutes								
			Restricting to Effects of					
	Return		DAX Only		FDAX Only		ODAX Only	
Security	Interval	Lags	Before	After	Before	After	Before	After
DAX	5 Min	1	6.20	18.07***	9.38	16.44***	9.00*	21.21***
FDAX	5 Min	1	41.96***	27.24***	18.23***	23.03***	53.84***	19.50***
ODAX	5 Min	1	55.17***	75.71***	55.38***	76.98***	20.30***	7.77
DAX	5 Min	4	17.22	267.28***	9.74	29.43***	77.50***	331.79***
FDAX	5 Min	4	51.48***	61.72***	16.97	22.73**	79.27***	50.20***
ODAX	5 Min	4	51.94***	209.76***	53.11***	204.21***	25.49***	19.07
DAX	15 Min	1	54.70***	193.50***	20.15***	41.01***	83.50***	159.92***
FDAX	15 Min	1	85.42***	32.22***	26.16***	22.80***	85.63***	57.83***
ODAX	15 Min	1	126.76***	257.86***	79.75***	252.77***	44.57***	31.07***
DAX	15 Min	4	28.15***	74.41***	13.56***	36.65***	65.22***	178.11***
FDAX	15 Min	4	41.92***	26.03***	23.63**	27.03***	107.71***	90.55***
ODAX	15 Min	4	183.28***	282.15***	148.44***	315.62***	16.20	31.82***
DAX	30 Min	1	36.32***	3.78	31.27***	14.28***	40.48***	27.55***
FDAX	30 Min	1	48.59***	20.28***	32.01***	15.25***	24.38***	56.10***
ODAX	30 Min	1	133.88***	164.71***	85.45***	171.08***	34.63***	20.43***
DAX	30 Min	4	10.71	31.30***	7.24	25.92***	29.73***	112.89***
FDAX	30 Min	4	15.01	28.03***	10.61	4.87	28.01***	88.04***
ODAX	30 Min	4	79.42***	159.99***	82.02***	87.48***	33.75***	23.61**

(table cont'd.)

Panel E: Put Options Estimated by Implied Volatilities of Past Hour

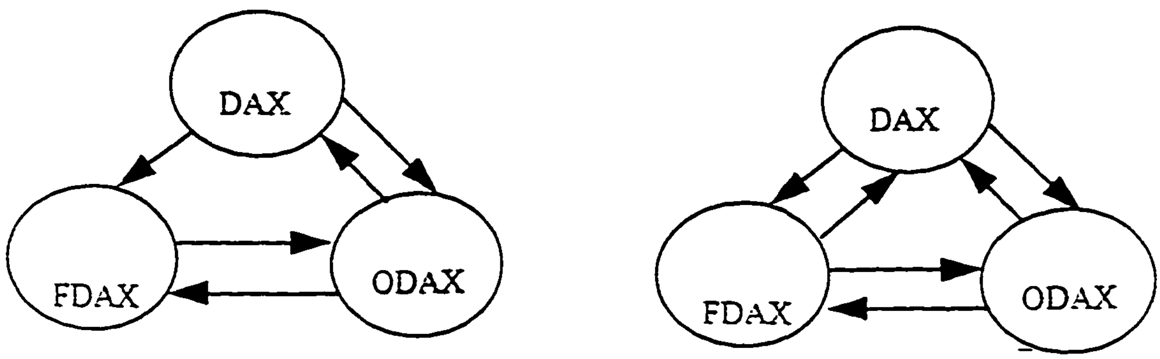
Security	Return Interval	Lags	DAX Only Before	DAX Only After	FDAX Only Before	FDAX Only After	ODAX Only Before	ODAX Only After
			Restricting to Effects of					
DAX	5 Min	1	5.98	18.23***	9.11	17.06***	52.95***	21.23***
FDAX	5 Min	1	40.61***	27.39***	18.05***	22.53***	54.46***	19.52***
ODAX	5 Min	1	59.66***	82.58***	55.06***	83.49***	17.51***	8.05
DAX	5 Min	4	19.13	269.03***	11.08	31.83***	75.73***	329.86***
FDAX	5 Min	4	50.15***	59.01***	19.04	22.78**	79.83***	50.91***
ODAX	5 Min	4	59.07***	202.33***	59.01***	206.08***	19.26	9.86
DAX	15 Min	1	54.14***	186.26***	19.52***	41.10***	81.52***	159.70***
FDAX	15 Min	1	81.09***	32.34***	26.41***	24.20***	86.75***	57.29***
ODAX	15 Min	1	154.02***	311.16***	106.53***	309.92***	36.31***	20.89***
DAX	15 Min	4	26.16***	71.22***	14.71	39.90***	76.23***	168.32***
FDAX	15 Min	4	39.57***	39.50***	23.96**	31.29***	122.20***	86.63***
ODAX	15 Min	4	173.40***	330.60***	120.93***	377.06***	14.84	27.10***
DAX	30 Min	1	30.72***	3.79	23.89***	14.50***	37.51***	25.50***
FDAX	30 Min	1	35.74***	19.91***	23.64***	16.09***	26.17***	27.89***
ODAX	30 Min	1	129.88***	130.39***	94.82***	137.98***	19.24***	20.40***
DAX	30 Min	4	10.22	45.91***	4.92	31.92***	34.86***	112.15***
FDAX	30 Min	4	9.86	47.35***	6.41	5.63	38.90***	61.46***
ODAX	30 Min	4	79.85***	244.34***	80.77***	151.06***	37.14***	27.12***

(table cont'd.)

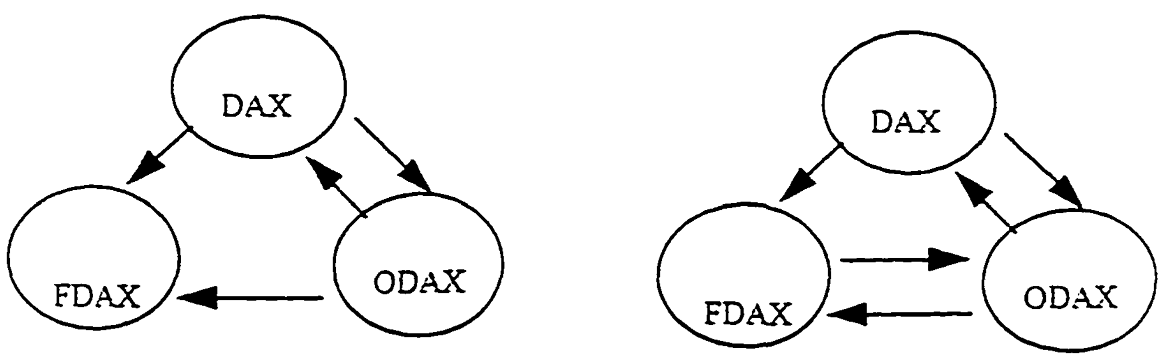
Panel F: Put Options Estimated by Implied Volatilities of Past Day								
			Restricting to Effects of					
	Return		DAX Only		FDAX Only		ODAX Only	
Security	Interval	Lags	Before	After	Before	After	Before	After
DAX	5 Min	1	5.37	16.57***	8.78	14.70***	56.10***	20.86***
FDAX	5 Min	1	40.79***	29.05***	20.81***	24.08***	56.70***	19.38***
ODAX	5 Min	1	59.18***	106.45***	49.49***	105.31***	23.86***	9.05
DAX	5 Min	4	20.96	270.76***	10.86	31.71***	76.22***	329.92***
FDAX	5 Min	4	38.01***	69.37***	15.94	25.53***	86.93***	48.98***
ODAX	5 Min	4	62.02***	257.08***	53.23***	256.10***	25.52***	11.04
DAX	15 Min	1	50.27***	201.02***	13.85***	43.19***	83.72***	157.54***
FDAX	15 Min	1	83.80***	33.26***	13.97***	24.05***	95.00***	58.25***
ODAX	15 Min	1	151.67***	266.68***	100.53***	237.74***	36.49***	18.57***
DAX	15 Min	4	32.81***	75.56***	12.59	36.25***	91.06***	181.02***
FDAX	15 Min	4	43.81***	30.64***	17.11	31.79***	131.58***	90.26***
ODAX	15 Min	4	172.11***	330.75***	160.50***	305.99***	6.66	37.26***
DAX	30 Min	1	33.85***	4.06	18.65***	13.61***	39.73***	26.27***
FDAX	30 Min	1	36.02***	20.31***	20.53***	16.06***	28.19***	29.41***
ODAX	30 Min	1	165.87***	195.97***	119.47***	194.93***	23.98***	16.01***
DAX	30 Min	4	8.96	51.40***	5.28	32.71***	34.17***	131.91***
FDAX	30 Min	4	11.30	49.27***	7.31	9.67	43.81***	60.28***
ODAX	30 Min	4	79.80***	264.86***	91.66***	130.00***	19.49*	23.88**

*** Significant at 0.1%, ** Significant at 0.5%, * Significant at 1%.

Before **After**



Five Minute Interval with One Lag

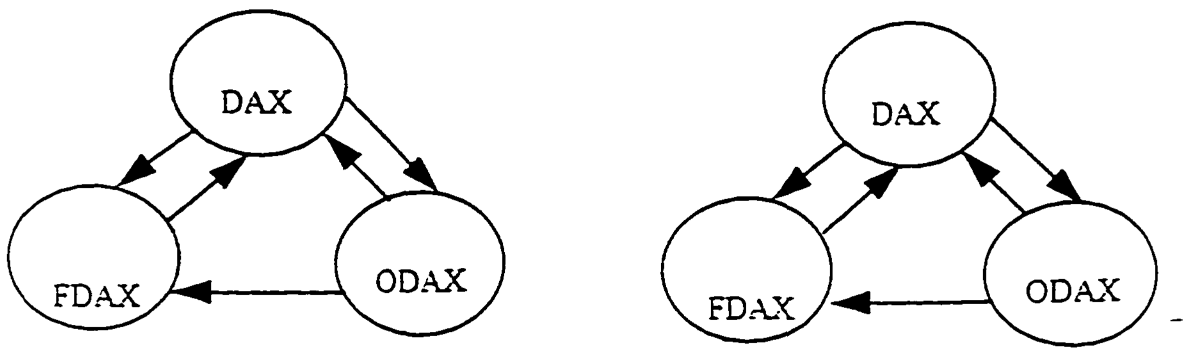


Five Minute Interval with Four Lags

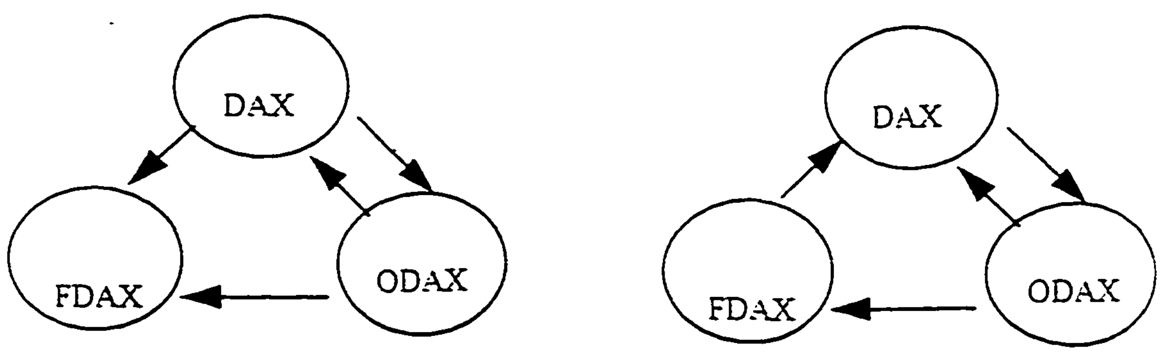
Figure 4.5

Volatility Spillovers Among the DAX Securities
Before and After the EMS Crisis: Five Minute Return
Arrows denote causal relationships.

Before **After**



15 Minute Interval with One Lag

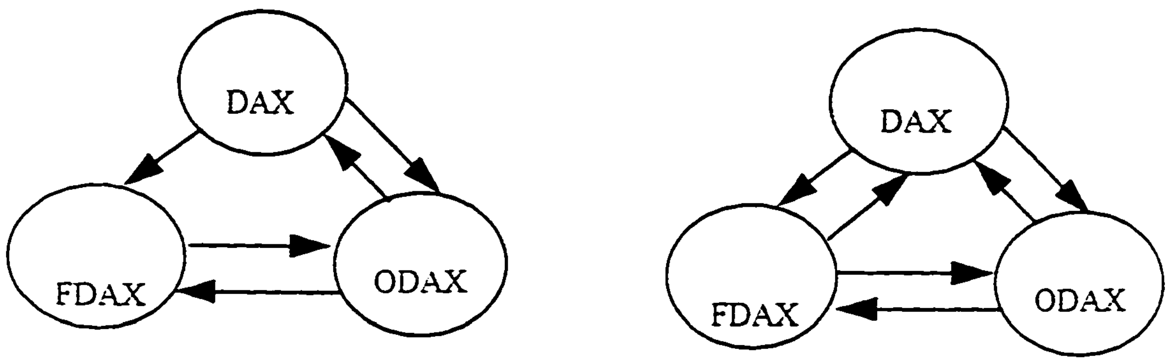


15 Minute Interval with Four Lags

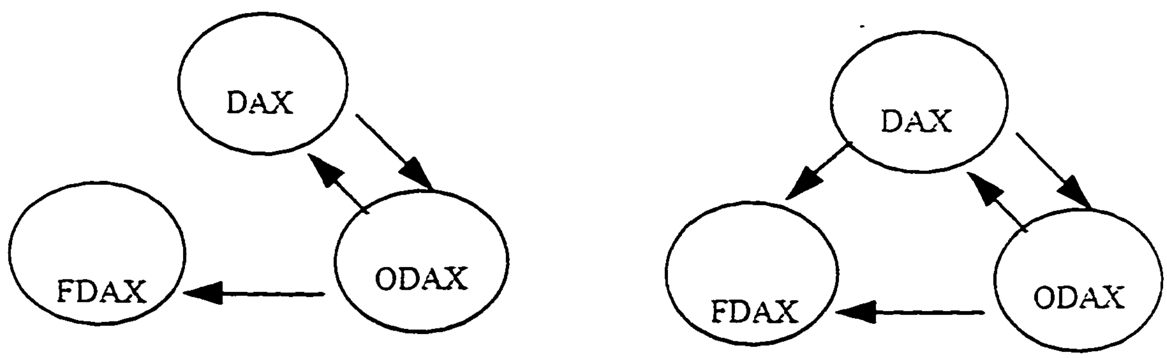
Figure 4.6

Volatility Spillovers Among the DAX Securities
Before and After the EMS Crisis: 15 Minute Return
Arrows denote causal relationships.

Before **After**



30 Minute Interval with One Lag



30 Minute Interval with Four Lags

Figure 4.7

Volatility Spillovers Among the DAX Securities
Before and After the EMS Crisis: 30 Minute Return
Arrows denote causal relationships.

effects are still significant. For the ODAX volatility, there is some evidence that the volatility spillover effects from the DAX and the FDAX increase after the EMS crisis. For both puts and calls, the Wald statistics become larger in the post-EMS crisis period. This shows that volatility of the ODAX market becomes more dependent on the volatilities of the other two DAX securities after the EMS crisis. Overall evidence suggests that the market for the DAX securities become more interrelated over time.

4.7 Summary

In this chapter, the issue of intraday volatility spillover is investigated. It is found that there does not exist a common volatility process among the DAX securities in short term intraday volatilities. However, a common volatility exists over a longer time span. Results from intraday volatility spillovers show that volatilities of the three DAX securities spillover to one another and there exists asymmetric effects between bad and good news. Furthermore, the markets for the DAX securities become more integrated after the EMS crisis. Overall results in this chapter support the notion that the three DAX securities as a whole perform the role of information processing.

Chapter 5

Summary And Conclusions

5.1 Introduction

This dissertation examines the intraday information processing mechanism in the stock index and the index derivative markets, by using the German market as an example. Previous literature in the study of information processing mechanism of index derivatives, e.g., Bhattacharya (1987) and Chan (1992), typically look at the spot index and one derivative only. In other words, the roles of other derivatives in information processing are left out. One objective of this dissertation is to fill this gap by examining the stock index, index futures and index options together. This study contributes to the literature by providing new empirical evidence on the intraday information processing mechanism among the index securities when the three index securities are considered as a whole system.

The choice of German data is due to data availability and its special features. First, the German stock index, the DAX, is a "total performance index." Different from other popular stock indices like the S&P 500, the DAX reflects stock distributions in its calculation. This special feature of the DAX allows for the adjustments for price changes caused by subscription rights, stock splits, and dividends. This point is particularly important since there is no need to estimate dividend yields in the calculation of the implied DAX from DAX options prices. Second, DAX futures and options are traded electronically. Thus, the reported time is the actual transaction time. One shortcoming in using U.S. data is that there could be delays in trade reportings. However, such

delays do not exist in Germany. Third, DAX options are European style options that make their valuation much easier. In these aspects, the German data offer a better arena than the U.S. data in the study of intraday information processing of stock index derivatives.

The dissertation consists of two essays; in which two issues in intraday information processing of index securities are studied. Specifically, intraday price discovery and volatility spillovers are examined. Essay one (Chapter 3) looks at the price discovery process while essay two (Chapter 4) explores volatility spillovers among the index securities.

5.2 Summary of Chapter 2

Chapter 2 presents the summary statistics of the intraday patterns of the returns of the index securities. These summary statistics show that there exists strong autocorrelation and ARCH effects among returns of the index securities. In addition, the returns of the index securities are not normally distributed. These features not only give a better understanding of the behaviors of the intraday return patterns of index securities. They also provide the theoretical support for various econometric techniques, e.g., EGARCH models and GMM estimation, etc., used in subsequent chapters.

5.3 Summary of Essay One

The first essay studies the intraday price discovery process among the index securities. Empirical work in the literature, e.g., Stoll and Whaley (1990), typically agree that index futures tend to lead the spot index. In other words, index futures have higher information contents. As noted in Fleming, Ostdiek and Whaley (1995) (FOW),

one important void in previous literature is that there is no explicit consideration of the roles of other derivatives in the information processing process. FOW extend previous studies by incorporating index options into the analysis of lead-lag relationship among index securities.

Similar to FOW, this essay also includes index options into the study of information processing mechanism of the index securities. However, this study extends FOW by looking at the degree of information sharing. In addition to looking at the lead-lag relationships among the index securities, this study also examines the degree of information sharing through the Gonzalo and Granger (1995) information sharing model. Apart from answering the question of whether index derivatives are more efficient in information processing than the spot market, this study addresses the relative efficiencies of index derivatives in intraday information processing.

Contributions of this essay lie in three major parts. First, more index securities are included in the analysis. Thus, a more comprehensive view about intraday price discovery among the index securities is presented. Second, this study also looks at information sharing. Degree of information sharing allows the study important of each security in the price discovery process.

It is found that index futures and the index tend to have larger information sharing than the options. The null hypothesis of the options not in the common factor is not rejected. In other words, option prices do not provide new information to the price discovery process. In terms of lead-lag relationships, the three index securities have

interaction effects. Returns of one security will have forecasting power over returns of other index securities and the options are not redundant in the lead-lag relationships.

5.4 Summary of Essay Two

The second essay explores the information transmission process among the index securities through volatility spillovers. Since the first essay looks at the information processing mechanism through the first moment, price discovery, the second essay extends the first one by examining the information processing mechanism through the second moment, volatility spillovers.

Volatility spillover refers to the process in which volatility of one market affects those of other markets. For example, Hamao, Masulis and Ng (1990), Lin, Engle and Ito (1994), Bae and Karolyi (1994) study volatility spillovers across financial markets. Developments in time series analysis allow for more robust estimation of the process of volatility spillovers. For example, the EGARCH model developed by Nelson (1991) can be used to model the asymmetric impacts of good and bad news on volatility. Empirically, several studies apply the EGARCH model to investigate the asymmetric effects of volatility spillovers between good and bad news, e.g., Koutmos and Booth (1995), Booth, Martikainen and Tse (1997) and Koutmos and Tucker (1996), etc.

Though there is a rich literature addressing the importance of volatility spillover across financial markets, the focus is on different national markets. Little is done to study intraday volatility spillovers among similar securities in the same national market. This chapter attempts to fill this gap by studying the volatility spillovers process among the index securities.

A closely related issue in volatility spillovers is whether financial markets share a common volatility process. Examining the presence of a common volatility process is useful since this is related to the information transmission mechanism. Empirically, Engle and Susmel (1993), Booth, Chowdhury and Martikainen (1996), and Tse and Booth (1996) study the existence of common volatilities in financial markets. Similar to the literature in volatility spillovers, these studies address the existence of a common volatility process among different national markets. This essay examines the existence of a common volatility process among the index securities in a domestic market.

In this essay, the following issues are examined: (i) whether there is a lead-lag relationship among the volatility of the stock index and the volatilities of the derivatives; (ii) whether there exists a common volatility process among the index securities; and (iii) whether the volatility spillover process in the index derivative markets is asymmetric.

This study contributes to the literature in the following ways. First, this study will extend previous studies by using intraday transaction data. Previous studies usually use daily data to study the volatility spillover process. Using daily closing data may induce additional biases into the analysis since intraday volatilities are ignored. Second, this study examines the volatility spillover process among the three index securities. Thus, a more complete analysis about the transmission of volatility in the same national market is given here.

It is found that there is no short term common volatility among the index securities. However, the three index securities share a common volatility process when a long time term is considered. In terms of volatility spillovers, volatilities of the three

index securities transmit to one another. Thus, information (volatility) from one market is useful in another market.

5.5 Implications and Conclusions

In summary, markets for the three index securities exhibit interaction effects in their price and volatility relationships. Consequently, all the three securities contribute to the intraday information processing mechanism. Thus, they should be considered as a whole system. To the practitioners, prices and volatility from one security are good sources of information to other securities. Though the ODAX prices do not provide information to the pricing of the FDAX and DAX, information from the volatility of ODAX is useful in predicting volatilities of the DAX and the FDAX. One important implication is that the derivatives help to make the market more information efficient. Therefore, the derivatives contribute to market completeness. Future research can be extended on the line of the usefulness of other index securities, e.g., future options, in market completeness.

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Vita

Raymond So was born in Hong Kong. He received his Bachelor and Master degrees in Buisness Administration from The Chinese University of Hong Kong. His areas of interest include investment, international finance and applied econometrics. Raymond loves history and plans to study for a Doctor of Philosophy degree in history after his retirement.

DOCTORAL EXAMINATION AND DISSERTATION REPORT

Candidate: Raymond Waiman So

Major Field: Business Administration

Title of Dissertation: Two Essays on Intraday Information Processing of Stock Index Derivatives

Approved:

Geoffrey Booth
Major Professor and Chairman

John M. Larkin
Dean of the Graduate School

EXAMINING COMMITTEE:

William W. Lane

Gary C. Sanger

Date of Examination:

February 26, 1997