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AN ECONOMETRIC INVESTIGATION BETWEEN VOLATILITY AND TRADING VOLUME OF THE HELSINKI AND NEW YORK STOCK EXCHANGES: A FIRM LEVEL APPROACH

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ABSTRACT: This Master's thesis focuses on the investigation of linear and non-linear dependencies between intraday volatility and trading volume time series of Nokia Corporation on the Helsinki and New York Stock Exchanges. The special properties of Nokia Corporation and the Finnish trading mechanism are discussed in this study. The recent trends and the capital co-movements in financial markets at the national and international level are considered in this Master's thesis. Markets' reaction, based on either fundamentals or noise, to new information is also discussed in this research.

This Master's thesis is based on extensive econometric analysis. Through several statistical procedures, the time series do exhibit certain similarities, but also clear differences. The volatility of Nokia ADS in New York seems to be greater on average than the volatility of Nokia A in Helsinki, but the variation in Helsinki is greater than in New York. The average changes in trading volume, and its variation, of Nokia ADS are greater than in the case of Nokia A. The difference in trading volume processes between markets is statistically different from zero, whereas the volatility series are not. The data consist of several outliers. The dates of most outliers can be traced to new information arrivals, announced by Nokia. By using linear models, approximately a third of the volatility (volume) variations can be explained by the variations of volume (volatility). The results are fairly similar within the stock markets. The unit root tests indicate that the series are stationary I(0) processes.

The Granger-causality models result in the conclusion that there do not exist coherent and stable causality relationships between the series, except the stable independence between the series on the NYSE. The Granger-causality relationships between the series change when different time lag specifications, observation periods or the significance levels are used. The non-existence of clear and stable causality relationships indicates that there is simultaneous information delivery across stock markets. This is, additionally, in accordance with the concept of informationally efficient markets. Recursive estimation provides support for the causality relationships: the small lag structures convey the best explanatory properties and the estimated parameters approach zero when the sample size increases. The impulse response functions tell that the responses to the stochastic shocks decay relatively quickly. The greatest reactions are found in the first days after the stochastic shocks, although some slow-motion responses are also present in this data.

Both of the trading on the HeSE and the NYSE must be taken into account when evaluating the intraday volatility and trading volume processes of Nokia Corporation. The dominant role of NYSE in determining the volatility and trading volume behaviour is not as evident as one may expect at the first glance. Helsinki trading is important because the new information flow is released typically during Finnish trading, when NYSE is closed.

KEYWORDS: Granger-causality, impulse response function, new information, recursive estimation, stationarity, stock markets, trading volume, volatility

SORJONEN, Juha, **EKONOMETRINEN TUTKIMUS VOLATILITEETTIEN JA KAUPANKÄYNTIVOLYYMIEN VÄLILLÄ HELSINGIN JA NEW YORKIN ARVOPAPERIPÖRSSEISSÄ: YRITYSKOHTAINEN LÄHESTYMISTAPA**, Helsinki, ETLA, Elinkeinoelämän Tutkimuslaitos, The Research Institute of the Finnish Economy, 1999, 99 s. (Keskusteluaiheita, Discussion Papers, ISSN, 0781-6847; No. 672).

TIIVISTELMÄ: Tämä Pro Gradu tutkii Nokia-yhtiön päivänsisäisten volatiliteettien ja kaupankäyntivolyymien välisiä lineaarisia ja epälineaarisia suhteita Helsingin ja New Yorkin Arvopaperipörsseissä. Tutkimuksessa keskustellaan Nokian ja suomalaisen arvopaperipörssin kaupankäyntimekanismin erityispiirteistä. Opinnäytetyössä pohditaan myös globaalien trendien ja pääomien yhteisliikkeiden merkitystä niin kansallisessa kuin kansainvälisessä kontekstissä. Markkinoiden reaktiot, perustuen joko taloudellisiin fundamentteihin tai kohinaan, suhteessa uuteen informaatioon ovat olleet tässä työssä pohdinnan kohteena.

Opinnäytetyö perustuu laajaan empiiriseen analyysiin. Monien tilastollisten proseduurien avulla on paljastunut, että yhtäältä aikasarjoilla on tiettyjä samoja piirteitä, mutta toisaalta myös selviä eroavaisuuksia. Nokia ADS:n volatiliteetti New Yorkissa on keskimäärin suurempi kuin Nokia A:n Helsingissä, mutta volatiliteetin vaihtelu Helsingissä on voimakkaampaa kuin vastaava vaihtelu New Yorkissa. Nokia ADS:n kaupankäyntivolyymin keskimääräiset muutokset ja muutoksien vaihtelu ovat suurempia kuin Nokia A:n. Volyymisarjojen välinen erotus poikkeaa tilastollisesti nollasta, kun volatiliteettiprosessien erotus on keskimäärin nolla. Aineistossa esiintyy lukuisia poikkeavia havaintoja, joista suurin osa voidaan jäljittää kaupankäyntipäiviin jolloin Nokia on julkaissut merkittäviä lehdistötiedotteita. Lineaaristen mallien avulla voidaan noin kolmannes volatiliteettien (volyymien) muutoksista selittää volyymien (volatiliteettien) muutoksilla. Tulokset ovat samansuuntaisia molemmilla markkinapaikoilla. Yksikköjuuritestit osoittavat aikasarjojen olevan stationaarisia I(0)-prosesseja.

Granger-kausaalisuusmallien tulokset eivät tue näkemystä koherenteistä ja stabiileista kausaalisuussuhteista. Poikkeuksena tästä ovat Nokia ADS-aikasarjat, joiden välillä on stabiili riippumattomuussuhde. Kausaalisuussuhteet muuttuvat riippuen käytetyistä ajallisista viiverakenteista, havaintojen lukumääristä ja merkitsevyystasoista. Tulokset tukevat näkemystä informaation saapumisesta markkinoille simultaanisesti sekä informatiivisesti tehokkaista markkinoista. Rekursiivinen estimointi tukee kausaalisuusmallien tuloksia: ainoastaan pienemmät viiveet ovat tilastollisesti merkitseviä ja mallien estimaatit lähestyvät otoskoon kasvaessa nollaa. Impulssi-vastine -funktiot puoltavat niinikään informaation nopeaa hintojenimeytymistä. Aikasarjat reagoivat verrattain nopeasti stokastisiin shokkeihin. Merkittävimmät sopeutumiset tapahtuvat tyypillisesti shokin jälkeisenä kaupankäyntipäivänä, joskin joissakin tapauksissa aikasarjojen vastinprosesseissa on hyvin pehmeitä ja hitaita sopeutumiselementtejä.

Analysoitaessa päivänsisäisen volatiliteettien ja kaupankäyntivolyymien kehitystä sekä New Yorkin että Helsingin noteeraukset on otettava huomioon. New Yorkin määräävä rooli ei ole niin selvää kuin mitä saattaisi ennakolta odottaa. Kaupankäynti Helsingissä on merkittävää, sillä Nokian julkistamat lehdistötiedotteet saapuvat tyypillisesti markkinoille suomalaisen osakemarkkinoiden aukioloaikana ja New Yorkin Arvopaperipörssin ollessa vielä kiinni.

AVAINSANAT: Granger-kausaalisuus, impulssi-vastine -funktio, kaupankäyntivolyymi, osakemarkkinat, rekursiivinen estimointi, stationaarisuus, uusi informaatio, volatiliteetti

CONTENT

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I was encouraged to deepen this subject during the seminars in Business Economics and Statistics and in the research seminar of the Department of Economics at University of Joensuu. I am very much obliged to the counsellors and participants of these seminars for valuable comments and suggestions.

The majority of the Master´s Thesis has been done during my stay as a exchange student in the Vienna School of Economics and Business Administration in the spring of 1997, so thanks belong to the Department of Economics and the Foreign Affairs Department of the University of Joensuu for financial support. I have been fortunate to have fruitful discussion about this study with Professor Manfred Fischer at the Vienna School of Economics and Business Administration and with Derivate Analyst Adrian Trapletti at Investmentbank Austria AG. Finally, I want to say that I remember friends of mine with thanks for inspiring discussions during writing this Master`s Thesis.

1. INTRODUCTION

Financial economists continue to seek a better understanding of the nature of stock price dynamics whereas global financial markets are experiencing considerable changes and development. Deregulation, globalization, co-operation between stock exchanges, growth of trading volumes, global online trading and maybe the most important aspect, development in information technology are good examples of the recent development of global financial markets. The role of emerging and thinly traded national stock markets have their own impact for the resource allocation in terms of obtaining the best risk-return relation. All these factors have together caused faster information delivery between national financial markets. In this sense, it can be expected that national stock exchanges are nowadays linked with each other much tighter than a decade ago. Due to the development and disappearance of different rigidities and frictions, it can be expected that global financial markets have become a more complex and unpredictable system.

However, numerous articles in the media have pointed out that there is a clear link and hence dependency between movements of Nokia Corporations´ stock prices on the Helsinki and New York Stock Exchanges (inter alia http://www.kauppalehti.fi). The trading volume behaviour has been of minor importance in evaluating dependencies of different stock series, however. Furthermore, it can be expected that the movements of financial time series, such as stock prices, do not remarkably differ from each other in different markets, otherwise the markets should be inefficient. An inefficient market indicates the possibilities for "free lunches", that is risk-free extra returns. In this sense the formulations and movements of "identical" stock prices should be analysed with a global stock markets perspective: it is a very interesting and demanding task to find out if stock price and trading volume series change freely and independently.

The structure of this Master's Thesis is the following: chapter two gives motivation and objectives for this research. Previous studies about the volume-volatility relationship with different approaches and procedures are briefly discussed in chapter three. This chapter will assist in understanding more deeply the relationship between stock prices and trading volumes. Global financial markets, the recent development and their relevance to Finnish stock markets are reviewed in chapter four. In order to picture the role of new information arrival in financial markets, the reactions in trading volume and volatility with respect to new information are discussed in chapter five. Additionally, the concept of informationally efficient markets, fundamentals and noise are briefly dealt with in the fifth chapter. The sixth chapter deals with data selection, a more detailed description and possible problems of the properties of volatility and volume series. Data description and basic descriptive statistics of time series are carried out and some special properties of Nokia Corporation are introduced.

Extensive econometrical analysis begins in seventh chapter. Basic linear regression analysis between volatility and trading volume series of the two national stock exchanges are carried out in chapter six in order to know if the volume-volatility relationship is positive, negative or zero. Analysis of stationarity of time serie is illustrated, analysed and criticised in chapter eight. Linear dependencies between trading volumes and volatilities and their cross-sectional dependencies are investigated after transformations of the time series. The investigation of linear dependencies is done by means of Granger-causality models in chapter nine. Recursive estimation is carried out in order to find the behaviour of the estimated parameters. Additionally, recursive estimation focuses on dynamic modelling of Nokia A´s intraday volatility. The last chapter of the empirical analysis, the tenth one, concentrates on non-linear dynamics, such as impulse response functions. The last chapter concludes estimated results and suggests some aspects for further research.

2. MOTIVATION FOR THE RESEARCH

2.1. The Inspirations of the Study

From a small stock market point of view, this Master's Thesis concentrates on mapping linear and non-linear dependencies between stock price volatility and trading volume of two stock markets with a firm level approach. Using the firm level, more precisely Nokia Corporation, can be justified by the great amount of articles in the Finnish media: Nokia's dominant role in the Finnish stock markets has been under lively discussion[1]. It has been argued and criticised that the Helsinki Stock Exchange (hereafter referred to as HeSE[2]) is a "satellite exchange" of the New York Stock Exchange (hereafter referred to as NYSE). However, most articles have been very qualitative and non-academic in their nature.

There exists at least two enough "deep" and fairly well applicable articles, written by Liljeblom (1995) and Hedvall, Liljeblom and Nummelin (1997). The article written by Liljeblom (1995) has worked as an inspiration and motivation for this study. She has investigated, by means of causality models, the stock price behaviours and their discoveries in three stock exchanges where Nokia Corporation is traded[3]. Liljeblom (1995) has stated that stock price determination on the HeSE influences the formulation on the SEAQ in London, but not vice versa. In comparisons between the HeSE and the NYSE, Liljeblom (1995) has not found any clear support of the causality relationships from the HeSE to the NYSE, or on the contrary, from the NYSE to the HeSE. In her article, Liljeblom (1995) has suggested that somewhat independent price determination may be due to the short time period used in the research. Furthermore, changes of exchange rates may have had their own influences when the NYSE USD-based American depository share (henceforth ADS) assets are converted to FIM-based. (Liljeblom, 1995)

The paper carried out by Hedvall et al. (1997) has focused on Nokia's price processes on the Helsinki and New York Stock Exchanges. Their objective has been to find out by means of error correction model (hereafter referred to as ECM) the relative contribution of the two markets for the price of Nokia Corporation. According to their results, both markets have significantly influenced to each other. According to the results of ECMs, they have suggested that the variation of the HeSE returns have been more driven by trading on the NYSE than vice versa. (Hedvall et al., 1997, p. 18)

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1 For example, Hedvall et al. (1997) have noted that occasionally Nokia Corporation has subsequently been the most traded stock series in the New York Stock Exchange.

2 The official name of Helsinki Stock Exchange will be HEX Helsingin Pörssi 1.1.1998.

3 Liljeblom (1995) has included the stock exchanges of London, Helsinki and New York into the models. The shares of Nokia Corporation are traded in the following stock exchanges (commencing year in parenthesis): Helsingin Arvopaperipörssi, Finland, (1915); Stockholms Fondbörs, Sweden, (1983); London Stock Exchange, UK, (1987); Frankfurter Wertpapierbörse, Germany, (1988); Bourse de Paris, France (1988); New York Stock Exchange, USA, (1994). (http://www.nokia.com) Trading activity of Nokia's shares is greatest in New York, but the home stock exchange in Helsinki is second biggest, measured as a percentage of total trading volume. However, the recent trend indicates that trading in Stockholm is increasing rapidly relative to the total trading volumes in different stock exchanges. For example in July 1997, 40 per cent of the total trading volume took place in New York, in Helsinki approximately 30 per cent and in Stockholm 14 per cent. The role of trading volume of Nokia Corporation has been minor in other Nokia listing stock exchanges, because it is the same e.g. for English investment banks where to trade: only the market liquidity and active trading are important (http: //www.kauppalehti.fi).

In spite of findings by Liljeblom (1995) and Hedvall et al. (1997) and additionally by the "common knowledge" of the Nokia`s behaviour within different stock markets, it is indeed essential to argue why the firm level approach has been chosen for this study. Additionally, it is worth to emphasise the shortcomings of some previous studies. Finally, it is a fundamental part of this research, to discuss what new and different information my study can offer with respect to the previous studies. My contribution is to bring deeper investigation and indication into the stock price *and* trading volume series of the most traded share series of HeSE[4]. These aspects are discussed in the following section.

2.2. Foundations for the Firm-Level Investigation

One of the main limitations of the earlier analyses of the volatility-volume relationship is that almost all have been performed with stock market index data. Results from thin markets with firm level approach are interesting for several reasons. Firstly, Lakonishok and Smidt (1988) and Lo and MacKinley (1990) have concluded that evidence from new markets reduces data snooping bias connected to financial models. Regardless of the development and the integration of global capital markets, studies on thin markets have been relatively sparse. Empirical results from smaller markets are of great importance for increasing the group of people who are planning to operate in the future in global financial markets.

Secondly, it has been stated that stock prices of companies move differently: one probable explanation is the preferences of institutional investors for large companies rather than small ones[5]. The preferences can be explained by better liquidity of shares of large companies. Pindyck and Rotemberg (1993) have found support for this finding. Pindyck and Rotemberg (1993) have suggested that the non-existence of co-movements among different company sizes may be due to higher risk premium of smaller firms relative to bigger companies. Martikainen (1994) has recognised the need to explore relationships on a branch basis in order to find more stronger dependencies. Thirdly, support has been found for an industry level effect: correlations between different industries have varied in the course of time, so different factors influence in different amounts the stock prices of exchange listed companies.

Because the size-of-the-company and branch-variations-effects can be avoided in this approach, the firm level investigation offers a more micro-type analysis rather than a macro one. Several papers have concentrated on stock markets as a whole, but few have taken a firm level approach. The interest relies on micro level, otherwise stock market indexes should be used in analysis instead of normal stock price series[6]. Findings mentioned above are good reasons for analysing the same company in different market places. Since it can expected that results from the empirical analysis may be inconsistent with the previous

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[4] The lack of the absence of trading volume series included into lead-lag investigations between assets or markets have been reported by e.g. Martikainen et al. 1994.

[5] Size of company can be measured e.g. by annual turnover or other related indicator of firm size. However, it is a well-known fact that smaller corporations may offer greater probabilities for bigger returns than large companies. This phenomena has often been associated to as a *firm-size anomaly*.

[6] Although there are some opinions about Nokia´s very dominant role in Finnish stock markets, Finland is not the only one in whose stock markets one or a few companies are dominant. European evidence for this are for example the Norwegian (Norsk Hydro) and the Dutch stock exchanges (Royal Dutch (Shell)).

studies, the role of Nokia Corporation is interesting. A dominating role on the Finnish markets and the trading on the NYSE will give exciting results. The main foundations and objectives are presented in the following section in order to clarify the aims and the objectives of this study.

2.3. The Aims and the Objectives of the Master`s Thesis

Regardless of clear findings of Liljeblom (1995) and Hedvall et al. (1997) there is a need for further analysis. The relationship should be analysed with long enough data in order to determine if the HeSE can be regarded as a "satellite stock exchange". In addition to the time aspect, different time spans are essential to determine the potential causalities and especially their stabilities.

Although there is an old Wall Street adage that "It takes volume to make prices move", the uncertain nature of the relationship between price variability and trading volume has led many researchers to examine the relationship between these time series in a single markets or asset. The asserted causality can be nevertheless questioned, numerous empirical findings have supported what will be called, as Karpoff (1987) has put it, "positive-volume-absolute-price-change-correlation". For that relation, Karpoff (1987) has reviewed extensive empirical evidence of previous studies in different markets and assets.

But on the one hand, the previous findings are no longer very informative because there has been great structural changes, development and integration in global markets. Some new econometrical methodologies are superior than the methods used in the past. On the other hand, findings of the previous studies are good reasons for up-dating investigation into whether these numerous findings still exist, have they changed or have they totally disappeared.

The deeper analysis and criticism of the previous studies and their methodologies are ignored since the focus of this research is concentrated on the different aspects of the volume-volatility relationship on the firm-level. Thus, the inference and critique of the previous market based studies are not longer very fruitful to be applied in this study. In addition, some studies are quite old, so a short description can be justified. The firm-level approach is quite unusual in academic research, so similar previous studies relative to this research are hard to find. However, the papers spelt out by Liljeblom (1995) and Hedvall et al. (1997) are good guidance, but unfortunately they are not applicable due to the different approaches: they have focused on price and return processes and I have chosen intraday volatility approach combined with trading volumes. However, the intraday volatility is the function of the daily price process, so in this context, a short review of these studies are worth to express.

It is important to include a trading volume variable into causality models. The analysis of trading volume is especially useful in understanding how new information is transmitted into stock prices. If trading volume is treated as a proxy variable for information flow, then the ability of the daily data of trading volumes to fully capture the information arrival effects on market returns would partly rest on the degree of efficiency of the stock markets. Lamoureux and Lasprates (1991) have confined to individual experiences of a sample actively traded stock returns. As Lamoureux and Lasprates (1991, p. 228) have put it:

> "This paper provides empirical support for the hypothesis that ARCH is a manifestation of the daily time dependence in the rate of information arrival to the market for *individual* stocks".

According to the Vice President of New York Stock Exchange Edmund Lukas, the listing at foreign stock exchanges increases trading activity in the home exchange[7] (http://www.kauppalehti.fi). In this context, analysis must be expanded to cover also trading volumes revealing valuable information about linear and non-linear dependencies of different assets.

Whereas many studies have concentrated on the *interday* basis, the volatility has been measured on a *intraday* basis in this research. This approach can be justified not only with the statistical properties of the time series, but also by the fact that the intraday volatility reflects the exact information and trading behaviour *during* the trading day. Analysis of the intraday volatility combined with the trading volume variable will give valuable information about stock market structure, and indication about "nervousness" and liquidity between the market of the interest. For example, as early as 1961 Marshall discovered that increased volume increases liquidity (smaller bid-ask spread). According to Marshall (1961), the size of the market matters: the greater is the volume in the market, the smaller the deviations in prices.

Behaviour of stock price series and trading volumes of Nokia A on the Helsinki Stock Exchange and Nokia ADS on the New York Stock Exchange will indicate the differences between different size stock markets: do the volatility and volume series share similar behaviour in the different stock exchanges or are there considerable differences? Secondly, by means of causality models linear dependencies between volatilities can be analysed in different markets. Moreover, volume-volatility causality, or vice versa can be investigated. An interesting task is to find how long lasting is the information compounded into historical observation. While the financial markets are typically considered effective, the role of past information would not be very valuable.

For the latest part in dependency analysis between volatility and volume series is non-linear estimation. It is interesting to explore whether additional valuable information about volatility and trading volume dependencies can be obtained from non-linear models: If the one of the four series is faced with stochastic shock, what can be said about the responses of the other three series?

Findings mentioned above justify the empirical econometric analysis of the dependencies between trading volumes and intraday volatilities in two stock exchanges. The next chapter will introduce some of the main reasons for the volume-volatility research. This is done by reviewing briefly the most important and the most often cited studies of this relationship. Review of the previous studies will give deeper understanding about the relationship between volume and volatility and thereby thorough and complete ground for the topic of this Master`s Thesis.

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[7] More detailed analysis of Nokia`s listings effects in terms of changed volatility and trading volume, see Hedvall et al. 1997.

3. THE REVIEW OF PREVIOUS STUDIES

3.1. Arguments for the Investigation of Volatility-Volume Relationship

An extensive survey of the previous studies of the volume-volatility relationship in the different market places, assets and methodological procedures has been carried out by Karpoff (1987). According to Liljeblom and Stenius (1997), the *positive* relationship between trading volume and volatility can result from heterogeneous beliefs (new information causing both price changes and trading), from sequential information arrival, or due to "price pressure" (perhaps created by liquidity costs or inelastic demand curve) (Liljeblom and Stenius, 1997, p. 424). More detailed aspects of volatility-volume space are worth to mention in order to clarify the important role of the this volatility-volume relationship in financial research. Usually four explanation for the relationship of trading volumes and stock price changes has been suggested in financial research.

Firstly, the volume-volatility relationship provides insight into *the structure of financial markets.* Relationship between prices and volumes can assist to discriminate between differing hypothesis about market structure. The models will predict various volatility-volume relations that depend on the rate of information flow to markets, how information is disseminated, extent to which market prices convey information, size of markets and existence of short sale restrictions. (Karpoff, 1987)

Secondly, the volume-volatility relation is important for *event studies*. Trading volume has associated to infer "informational content" of an event, and in addition to whether investor's interpretations of new information has been similar or have they varied among investors. (e.g. Beaver, 1968; Rogaski, 1978; Morse, 1981; Pincus, 1983; and Lakonishok and Vermaelen, 1986) In other words, price changes have interpreted as the evaluations and the predictions of investors about new information, while the corresponding volumes have regarded as an indication of the extent to which investors disagree about the direction of new information. This can be justified by words of Beaver (1968):

> "An important distinction between the price and volume tests is that the former reflects changes in the expectations of the market as a whole while the latter reflects changes in the expectations of individual investors." (p. 69)

It is a well-known fact that interim reports offer valuable information not only of the past progress but also for the future of corporations (e.g. Martikainen 1995). Bamber and Youngsoon (1995) have shown in their event study that there are a positive relation between the magnitudes of price and volume reactions (on average) near a quarter of the announcements. These findings have suggested that trading volume is likely to be high relative to price reaction when the earnings announcement generates differential belief revisions among investors, but a small average market belief revision. (Bamber and Youngsoon, 1995)

Maddala and Nimalendran (1995) have reported earnings surprises have a positive impact on prices and volumes and a negative in impact on spreads. Furthermore, *the short-run effects* of earnings announcements surprises to prices, volumes and bid-ask spreads have tended to be greater than *the long-run effects.* Comparing different corporations with varying market values, Maddala and Nimalendran (1995) have concluded that the small-market-value firms have faced a decreased volume and an increased spreads with the earnings surprises, whereas trading volume series have increased and spreads decreased for the large-market-value firms. These notes have suggested generally consistently with models of an asymmetric information (Maddala and Nimaledran, 1995, p. 241). Additionally, their findings give additional support for the investors´ preferences towards large companies.

Brush (1996) has pointed out that stock markets may face so called *"pre-announcement"* period before an interim reports season. That is the period when companies report that the actual earnings numbers to be formally announced later will differ from what has been expected by market participants. During this season, volatility may be abnormally high, but on the other hand price changes can be very stable and low, if market consensus exists and market participants are waiting for the real releases of interim reports.

The Finnish evidence of stock price behaviour around earnings announcements has been presented by Martikainen (1995). In his article, Martikainen (1995) has illustrated that returns tend to increase one day before surprising positive earnings announcements. An interesting event study investigation have been gone through by Pursiainen and Viitanen (1996)[8]. They have found out that there was two clear "winners" in telecommunication companies (Qualcomm and Motorola), one moderate (Nokia) in telecommunication industry. For the two other companies, Ericsson and Benefon, the event have not affected at all in terms of obtaining abnormal returns during 30 days before and after the press release. (Pursiainen and Viitanen, 1996)

Schadewitz (1994) has carried out an investigation of bid-ask spreads and trading responses to interim reports releases on the HeSE. Schadewitz (1994) has suggested that the bid-ask spread represents information asymmetry between investors. The information asymmetry has been proxied by the spread. According to his results, the spread and hence the asymmetry has been wider before the news releases than after the releases. Schadewitz (1994) has concluded that the market responses have been somewhat different and depended on the content of the report on the Finnish stock markets.

In order to investigate stock price behaviour and trading volume with an event-study approach, it is essential to pay attention to the possibility of rational expectations and analysts´ forecasts of e.g. earnings announcements or other news. Modelling expectations in the two markets is very difficult task. The expectations may vary among investors due to different investment horizons, return requirements, investment policies and investors´ own positions. Moreover, Webb (1994) has stated that the importance of press releases and other "news" may vary in the course of time: sometimes "regular" announcements are in minor interest among investors and "surprising", i.e. unpredictable and unexpected news are considered much more important.

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8 Their event study has focused on the US cellular operators decision for choosing American CDMA cellular network technology instead of European GSM technology. Pursiainen and Viitanen (1996) have found intraindustry relationships between different stock exchanges by comparing abnormal returns between telecommunication companies Benefon, LM Ericsson, Nokia, Motorola and Qualcomm.

The choice of surprising news for an event study purpose is difficult, because Nokia Corporation has released numerous press releases during the observation period (http://www.nokia.com). These facts suggest for concentration on longer time period behaviour of stock prices instead of the event study with very short time span. However, to avoid possible long-run dependent problems, the data has divided into two subperiods in order to explore also effects of the shorter run.

The third factor in motivation for the volume-volatility study, is its significant implications for *the research of futures market.* In futures contracts, volatility affects on trading volume (Cornell 1981). Crain and Lee (1996) have carried out clear evidence in the U.S. wheat markets volatility is transferred from the futures markets into the spot markets. Today´s volatility in the spot markets is significantly related to past volatility up to at least 10 days lags. However, Crain and Lee (1996) have emphasised that more recent volatility shows greater impact than more lagged volatility. The spot volatility has also Granger-caused the volatility of futures markets, but the effects reach only up to three or four lags. The impact of futures markets on the spot markets has been clearer and more persistent than the impact of the spots on the futures. (Crain and Lee, 1996) Holmes (1996) has investigated whether the futures trading has beneficial impacts on the spot markets on the thinly traded futures contracts, that is FTSE Eurotract. According to Holmes (1996), despite of low volume, the existence of futures trading has improved the rate at which information has impounded into spot prices and reduced persistence.

There has been also lively debate over whether the existence of trading in futures market has stabilised or destabilised the volatility on spot markets: an increase in trading volume on the futures markets may be due to increased demand for *hedging or speculation*, which may therefore have different effects on the spot volatility. Stabilising effects on the spot markets on the one hand have been reported by e.g. Edwards (1988) and Weaver and Banerjee (1990), but on the other hand destabilising effects have been presented e.g. by surveys of Chatrath et al. (1995), Kocagil (1994) and Driskill et al. (1991). On a commodity market basis, Stein (1991) have found speculation is destabilising in the soybean and wheat, but not in corn, cattle and pork future commodity contracts. For the reference of distinction of "stabilising" and "destabilising" speculation, see e.g. Stein (1991).

The last explanation for the volume-volatility relationship has been the debate over *the empirical distribution of speculative prices.* It has been shown by several studies that the distributions of stock prices, particularly the daily changes, are leptokurtic which implies that the distribution is excessively peaked around the zero and too thick in the extreme tails relative to the Gaussian distribution (Clark, 1973; Epps and Epps, 1976; Tauchen and Pitts, 1983; and Altug and Labadie, 1994) There is also a significant body of evidence of conditional heteroscedasticity and the dependence of higher order moments on time-varying conditioning sets in the distribution of the daily price changes. (see, e.g. Bollerslev, 1986 and Nelson, 1991)

The non-Gaussian nature of the daily price changes is considered something as a paradox. The daily price changes are a sum of many within-day independent price movements, triggered by many new pieces of information about market fundamentals. For example, Clark (1973) has suggested that trading activity varies randomly from day to day. On some days, much of new information flows to markets and the price takes few steps within a trading day. Consequently, the daily price should be modelled as a mixture of Gaussian random variables such that the daily prices are the sum of a random number of the within-day changes. (Strong and Walker, 1987) In this context, it is worth to point out the concept of *the mixture of distribution hypothesis (MDH)* which suggest that a data is sampled from a mixture of distributions that have different conditional variances (Clark, 1973 and Epps and Epps, 1976). As Karpoff (1987) have put it

> "... it appears price data are generated by a conditional stochastic process with a changing variance parameter that can be proxied by volume. Knowledge of the price-volume relation can then be used ... to measure changes in the variance of the price process ..." (p.110)

The hypothesis concentrates on the distribution of speculative prices which has assumed to be kurtotic and links information flow, volume and price volatility. A further development is *the sequential information hypothesis*, developed by Copeland (1976). Ragunathan and Peker (1996), among many others, have pointed out that the hypothesis implies also a positive correlation between price variability and trading volume. An explanation for the positive correlation has been argued by the distribution of speculative prices. In this context, the MDH is usually regarded as a reason for the departure of price change from the normal distribution. (Karpoff, 1987)

The correlation between volume and absolute change of prices have appeared to be typically positive both in equity and futures markets. Nevertheless of universal findings of the positive correlations, some of these findings have indicated that the correlation is weak: there is large body of evidence to suggest that the short-term price changes in financial markets are nearly unpredictable given the past prices. Thus, a short review of the role of time aspect in the volume-volatility relationship is carried out in the following section.

3.2. The Time Aspect of the Volume-Volatility Relationship

Tauchen and Pitts (1983) have distinguished the relationship between price changes and trading volume *in the short and long-run*. The short-run relationship builds on a reverse causation, i.e. from price changes to volume. Godfrey et al. as early as in 1964, have reported the positive correlation between daily volume and daily high and daily low on intraday basis. The positive relationship between stock returns and trading volumes on interday basis has been firstly documented by Ying in 1966.

Support for the positive dependence have been presented by Granger and Morgenstein (1970). They have reported that daily volume correlates with squared difference between daily opening and closing prices. Additionally, Epps and Epps (1976) have suggested that trading volume moves with measures of within-day price variability because the distribution of transaction price change is a function of trading volume. The similar positive correlation has been found more lately, for example, by Rogalski (1987), Harris (1986), Richardson et al. (1986) and Comiskey et al. (1987). The positive relationship between absolute price changes and trading volumes have reported e.g. by Osborne (1959), Wood et al. (1985) and Harris (1986).

Empirical studies, e.g. Garbade and Silber (1979), Tauchen and Pitts (1983), Cohen et al. (1987) and Pagano (1989), have researched *the long-run relationship* between trading volume and price volatility. The results have indicated that an increase in trading volume will be accompanied by a drop in volatility. Additional empirical support for the negative relationship between trading volume and volatility have been found in cross-country comparisons, e.g. by Cohen et al. (1978) and in comparison of issues exhibiting differences in trading frequencies on the same exchanges e.g. by Pagano (1985). Berglund and Liljeblom (1990) have suggested that the main reason to expect a decrease in volatility in response to an increase in volume is the fact that an increased volume is usually accompanied by an increase in number of traders. On this basis, some attention have to paid to the aspect of number of traders.

3.3. The Number of Traders

An interesting point of the volume-volatility framework has been carried out by Tauchen and Pitts (1983). They have observed that the variance of daily price changes and the mean of daily trading volumes depend on three factors: firstly, the average daily rate at which information flows to markets, and secondly, the extent to which traders disagree when they respond to new information. However, Tauchen and Pitts (1983) have questioned the assumption about regarding these factors as a constant over time[9]. For the latest, the number of active traders in markets has regarded as a one important factor to determine the volume-volatility relationship.

Tauchen and Pitts (1983) have found out that trading volume is strongly trended (appeared to grow exponentially!) during observation time January 1976 - June 1979 in the U.S. stock markets. In this context, the forthcoming results from Nokia´s point of view of the volume-volatility relationship may be very misleading, because it is not reasonable to assume the existence of exponentially growing trading volume in the long-run. It has been shown by Tauchen and Pitts (1983) that there exists some interaction effect between traders. The interaction leads to a decreased trading volume per each trader when trading volume is growing in markets. However, Tauchen and Pitts (1983) have noted that the effect is relatively small compared to the degree of increase in the trading volume of markets. The small interaction effect has resulted to the assumption of somewhat constant or upward trended of the numbers of traders. (Tauchen and Pitts, 1983)

3.4. The Role of Speed of Information Arrival

In spite of the fact that the positive relationship between stock prices changes and trading volume is well documented and dominates the results of financial research, the speed of information arrival has received much less attention. In terms of stating whether the information arrival is *simultaneous or sequential*, financial research has not paid much attention to this aspect.

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[9] Tauchen and Pitts (1983) have noted that these constant assumptions may cause some errors in empirical analysis. This can be justified by autocorrelation structure in prediction errors of estimated models. Tauchen and Pitts (1983) have suggested that autocorrelation structure can be partly explained by slow-moving forces that determine the rate of flow of new information to markets.

According to Smirlock and Starks (1988), the hypothesis of contemporaneous relationship between stock price changes and trading volumes is called as *a simultaneous information arrival hypothesis* (SIM). In this case, the complete information equilibrium (defined as the equilibrium when all traders have the information) is obtained in a single trading round and no intermediate equilibria are assumed to exists. (Martikainen et al., 1994)

The hypothesis of a lead-lag relationship between price changes and trading volumes is referred to as a *sequential information arrival hypothesis* (SEQ). According to this hypothesis, investors receive new information one at a time and trading occurs after each reception. Thus, an intermediate equilibria are assumed to exist under this hypothesis. An illustrative example of SEQ-model has been presented by Copeland (1976). Martikainen et al. (1994), among many others, have suggested that the model is based on the asymmetric information between investors and the information is disseminated to only one trader at a time. This causes a one-time upward shift in each "optimistic´s" demand curve by a fixed amount, and an equal downward shift in the demand curve of a pessimist. Trading occurs after each trader receives the information, but uniformed traders do not infer the content of the information from trader´s actions. (Martikainen et al., 1994)

The lead-lag relationships between stock prices change and trading volume series have received much less attention than the contemporaneous relationships. For example, Smirlock and Starks (1988) have found out empirical evidence of the SEQ hypothesis. However, they have also reported some evidence against it: in this sense the results are somewhat inconclusive. Consistently with the results of Smirlock and Starks (1988), Martikainen et al. (1994) have represented support in favour of the sequential information hypothesis suggesting asymmetric information within investors in the Finnish stock markets.

Information delivery must be uniform within market participants, otherwise some investors may gain additional advantages compared to other "non-informed" investors. Coincidentally, there is going on a lively debate of the non-simultaneous information delivery within market participants in Finland. The HeSE has emphasised that information releases must reach media and stock exchanges at the same time in order to further delivery. More discussion and articles about this necessary request for the informationally independent stock markets see *inter alia* http://www.kauppalehti.fi.

It is probable to observe simultaneous large volumes and large price changes - either the positive or the negative relationships - in financial data. These large changes can be traced to their common ties to information flows (as in the case of the SEQ) or to their common ties to a directing process which can be interpreted as flow of information (as in the case of the MDH). Relatively large costs of short positions - where it is possible - provide an explanation for that trading volume associated with a price increase generally exceeds that with an equal price decrease. This comes from the notation of costly short sales restrict some investors´ abilities to trade on new information.

In spite of the numerous studies of the linear volatility-volume relationship and the different speed of information concepts, a non-linear relationship between these variables is more than probable. Thus, some evidence of the non-linear dynamics is essential to show in order to get more deeper conception of the volatility-volume framework. Some evidence of the non-linear dynamics between volatility and volume is drawn in the following section.

3.5. Non-Linear Models

Similar approach of the MDH is a non-linear ARCH-family (autoregressive conditional heteroscedasticity)[10] models which have experienced great success among financial research[11]. The ARCH -process is appropriate for speculative prices for it allows volatility to persist by assuming an autoregressive process on conditional variance. The ARCH-family and its several extensions are the latest and the often used methodology to map the relationship between stock price volatility and trading volume and *per se*. Moreover, the ARCH-family models have achieved interesting results in the forecasting of financial time series. (Engle, 1995 and Rossi, 1996)

Lamoreux and Lastrapes (1990) have assumed that the presence of the ARCH-effect in returns data is due to the mixture of distribution hypothesis with the daily arrival of information as a mixing variable. Their objective has been to prove that the ARCH-process can capture time series effects of the mixing variable, i.e. volume. For example, Gallant et al. (1992) have shown that volatility and volume are highly persistent and contemporaneously correlated. The persistence of volatility itself has generated a large literature using different ARCH-model specifications. An extensive survey of the ARCH-models and the recent development has been carried out by e.g. Bollerslev et al. (1992), Engle (1995) and Rossi (1996).

Brailsford (1994a) has tested the relationship between trading volume and stock return conditional volatility using the GARCH(1,1)-model in Australian stock markets. He has concluded for absolute returns that the results provide a strong support for GARCH(1,1) specification. The results have been much weaker in the case of squared returns. For the volume serie, measured as the number of traded shares, the results have found to be insignificant. In their study, Ragunathan and Peker (1996) have reported some evidence of volatility being influenced by its own lagged values. In standpoint of trading volume, the results have suggested that positive volume shocks have a greater impact on volatility than negative shocks. (Ragunathan and Peker, 1996)

Martikainen et al. (1994) have analysed linear and non-linear dependencies between stock returns and trading volumes in the Finnish stock markets. Consistent with the earlier results from the US markets, their findings have indicated significant bi-directional feedback between the volume and the stock prices in time period 1983-1988. By means of Granger-causality models and different specifications of the MA-GARCH-models, Martikainen et al. (1994) have found structural changes in the Finnish stock markets with different time spans: the bi-directional feedback effect between the volume and the stock returns has found in the first sub-period. In the latter sub-period Martikainen et al. (1994) have not found any causalities within the time series. Martikainen et al. (1994) have suggested that

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[10] The ARCH-model has been firstly introduced by Robert F. Engle (1982) in his classic Econometrica article "Autoregressive Conditional Heteroscedasticity with the Variance of United Kingdom Inflation".

[11] An earlier note of the nonnormal distribution of speculative prices is for example Morgan (1976). Morgan (1976) has not only found the stock return distribution to be heteroscedastic, but also that trading volume can play an important role in explaining the variance of return distribution.

the variation of the results in the course of time may be due to the development of the Finnish financial markets. Their findings have indicated that the Finnish stock-return-trading-volume relationship has become more similar to the US financial markets. Furthermore, the results are consistent with the classical study of Karpoff (1987) which has revealed that the size of market may affect the price-volume relationship.

Hiemstra and Jones (1994) have investigated a non-linear Granger-causal relationship between aggregate trading volumes and stock prices. They have shown that the trading volume non-linearly Granger-causes the price movements. These findings are in contrast those of Gallant et al. (1993) who have not found any evidence of the feedback from volume shocks to either the conditional mean or volatility of stock prices. Hiemstra and Jones (1994) have observed that trading volume Granger-causes changes of stock prices, but the effects are concentrated in the higher order moments (above 2) and are transient in their nature.

Several studies have also begun to examine a non-linear dynamic structure of the price-volume relationship. Hiemstra and Jones (1993) have found a non-linear relationships between trading volume and volatility processes which can not be easily examined through standard models of persistent volatility. Investigation for a joint volume-volatility process, Gallant et al. (1993) have used a non-linear impulse response function (hereafter referred to as IRF). Several papers have also analysed changes in a conditional predictability conditioned on trading volume serie, e.g. Morse (1980), Antoniewitz (1992), LeBaron (1992) and Campbell et al. (1993). LeBaron (1993) has investigated the joint dynamics and the stability of stock prices and volume series of CRPS value weighted index with daily observation from 1962 through 1988. By using local linear models, he has analysed the stability of the joint processes in different regions in the volatility-volume space. LeBaron (1993) has suggested that some small shocks may be temporarily amplified, but they will eventually dissipate. However, his findings do not suggest that there would be a deterministic chaos in the volume and volatility series, the results are just showing that there is a local instability (LeBaron, 1993, p. 8). The fitted models have indicated that the two series are persistent and there is a channel from the volume to the future´s volatility. However, as LeBaron (1993) has stated

> "The channel varies dramatically from low to high volume periods. During low periods it is negative, and during high periods it is positive." (p. 9)

Tauchen et al. (1995) have applied a dynamic impulse-response analysis of long panel data of actively NYSE traded companies such as Boeing, Coca-Cola, International Business Machines (IBM) and Minnesota, Mining and Manufacturing (MMM). Their study has focused on the persistence properties of stochastic volatilities, the asymmetric character of conditional variance functions and the characteristic of various non-linear price-volume interactions. Tauchen et al. (1995) have suggested that the degree of the persistence in volatility is smaller than detected in the broad stock index prices. The volume shocks have found out to respond non-linearly to the price shocks and the volume increases whatever the sign of the price shock has been and then damps very slowly back to baseline.

Tauchen et al. (1995) have shown that trading volume shocks affect stock prices, but the effects are very transient and confined to the higher order (above second) conditional moments. However, in contrast to some recent evidence on the broad market indexes, the local history of volume serie appears not to influence the serial correlation properties of four stock price series. (Tauchen et al., 1995)

More recently, Sharma et al. (1996) have studied the relevance of results between micro and macro level approaches in order to find out if it is reasonable to assume that time varying and other non-linear effects are similar in a company level and in a stock market level. Sharma et al. (1996) have stated that differences can casually exhibit and then similar GARCH-effects cannot be expected between the market and the firm level approaches.

Sharma et al. (1996) have argued that for individual stocks, volatility is generated by firm-specific factors and market-wide factors, both of which affect trading volume. This should make trading volume a good proxy for information which contributes to conditional heteroscedasticity. In terms of market returns, the volatility is generated by the market-wide factors, but the volume by both the firm-specific as well the market-specific factors. The firm-specific volatility usually swamps systematic volatility of individual stocks returns. On the other hand, the trading volume of markets probably depend less on the firm-specific factors and more on the market-wide factors. This should make the trading volume a poor proxy for information arrival that contributes conditional heteroscedasticity to the market-wide returns. (Sharma et al., 1996)

Not only the firm level and the market-wide factors influence on stock price behaviour. Nokia Corporation is a multinational telecommunication company which operates globally and is affected by the global factors, such as its actions of competitors, raw material prices, exchange rates, international and national logistics systems and development of emerging market and their infrastructural reconstructures. Thus, it can be expected that Nokia is more sensitive to changes in global economy and megatrends rather than the national economical circumstances. In this international point of view, it is essential to note some aspects of international capital movements. This is done shortly in the following chapter.

4. INTERNATIONAL CAPITAL MOVEMENTS: COMMON FEATURES OR INDEPENDENCE?

4.1. The Evidence of Co-Movements in Financial Markets

National financial markets have experienced a rapid deregulation in recent years, which has led to increased financial transactions between the domestic markets. Investing has then became more and more global. The integration of international financial markets means the linking of the domestic financial markets (Stein, 1991, p. 15). In spite of the recent development of the national stock markets, there are evidently certain differences in the economical and institutional environments, such as a legislation and a market mechanism between large and small markets, however[12].

The benefits of the capital market integration have long been recognised. The integrated financial markets allow capital to flow to where it can be most productive. However, the markets have faced different shocks. The extent to which the price changes of global stocks influence the rest of the national markets depends on the nature of the forces behind buying and selling and on the importance of overseas stocks relative to the national markets. Especially, the European national stock markets have high percentage of overseas stocks[13]. However, according to Puttonen (1995), the probability for the higher volatility in terms of a high decrease or an increase of stock prices have been relatively the same. Further, the "jumps" have not followed any clear (technical) cycle in the long run. Nowadays this is a well-known and accepted fact in financial markets[14].

There is indeed some dichotomy between the persistency: on the one hand, many researchers have reported *the long-run dependencies* in daily stock returns between different markets and assets. But on the other hand, there exist a great amount of evidence for *the long-run departures*. Maybe the most common swings are speculative bubbles, fads and time varying conditional returns. (Cheng and Lai, 1995). Further, the recent studies have provided conflicting results. For example, Marlliaris and Urrutia (1992) have not find any lead-lag relationships for the world's six major stock market indexes for before and after the 1987 market Crash. In contrast to the Marlliaris and Urrutia's findings, Arshanapalli and Doukas (1993) have reported evidence of increased degree of international co-movements among price indexes on the stock exchanges of Germany,

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12 The segmented nature of stock markets can be explained e.g. by the existence of imposed barriers to prevent free flow of capital, market imperfections in the form of high transaction costs for foreign investors, information differences between markets, such as differing accounting conventions. Due to the differences in information delivery and absorptions across national stock exchanges, several empirical studies have indicated that different markets absorb information with different speed. Therefore, the varying information absorption creates linkages for lead-lag structures for the pricing mechanism of assets. (Pynnönen et al., 1994)

13 According to Blackman et al. (1994), several European stock markets have extremely large foreign representation, for example, Germany 46 %, Amsterdam 48 %, Geneva 70 %. Corresponding percentage in London is 21 %, New York only 5 % and Tokyo 7 %.

14 Deregulation have their critics and defenders. The critics claim that there is too much price volatility. The defenders claim that the deregulation serve important economic functions. The price volatility simply reflects the variability of the fundamentals of the economy or the underlying asset; and the price of asset reflects all available information about future events, i.e. the fundamentals. (Stein, 1991) However, for the industrial economies, the volatility of capital flows relative to national outputs seems to be no greater than in the late 1950s (Fieleke, 1996, p. 59).

France, Japan, the United Kingdom and United States after the October 1987 period. Additionally, they have found out that the U.S. stock market has had a considerable impact on several other domestic markets after the Crash. Smith et al. (1993) has applied rolling Granger-Causality test to support evidence of no causal relationship among the major stock market apart from few episodes of unidirectional causality running from the US to other countries.

Significant relationship between the returns of different stock markets have been reported by many authors. In their early paper, Makridakis and Wheelwright (1974) have investigated the short term stability between 14 stock indexes. They have reported that the co-movements of the different stock exchanges seem to be random processes. Similar conclusions have been drawn e.g. by Hillard (1979). Market dependency studies within foreign exchange markets have been carried out e.g. by Engle and Susmel (1993). More recently, Chaudhuri (1997) has provided evidence of the long-run relationship among six Latin American emerging markets.

However, the studies in the end of eighties and in the beginning of nineties have provided evidence of a higher level of stability in co-movements of international stock markets (e.g. von Furstenberg and Nam Jeon, 1989; Grinold et al., 1989; Meric and Meric, 1989; Lo, 1991; Malkamäki et al., 1991; and Pindyck and Rotemberg, 1993). A general trend seems to be that stock prices in different countries tend to move more similarly in the 1980`s and 1990´s than before. Several studies have reported that the co-movements have significantly changed after the October 1987 Crash. Typically, stronger interrelationship have been found after the Crash by many authors. (Martikainen and Puttonen, 1991)

Blackman et al. (1994) have carried out a study which operated long-term statistical relationships between 17 prices of share on different national stock markets. Blackman et al. (1994) have stated that the institutional and technological changes which occurred in the early 1980s have to be carefully evaluated. Such a relationships have been unlikely before 1980, markets are nowadays expected to move together (Blackman, et al. 1994, p. 297). They have suggested that the structural and the institutional changes have altered the relationship between the national stock markets and hence brought closer to each other.

Some papers have focused on the transmission of volatility between stock markets. For example, Engle and Susmel (1993) have observed a common volatility process for several stocks on weekly data for the period 1980-1989. Moreover, Hamao et al. (1990), and Koutmos and Booth et al. (1994) have observed significant volatility spillovers between US, UK, and Japanese stock markets. A similar volatility spillovers from US stock markets to Japanese markets have been discovered for example by Lin et al. (1991). Evidence of Pasific basis of integration investigations and responses to the different shocks and, see *inter alia* Bos and Fetherson (1997).

Monadjemi and Perry (1996) have carried out an investigation on the European basis. They have studied responses of four national share prices (Belgium, Britain, France and Germany) to the influences of major international share markets, domestic output and interest rates. According to their results, all countries have had a positive and significant responses of share prices to movements of foreign share prices and a negative and significant responses to changes in domestic interest rates.

A firm-level investigation has been spelt out by Harris (1995). Harris (1995) has estimated an error correction model using synchronous transactions data for International Business Machines (IBM) from the New York, Pacific and Midwest Stock Exchanges. He has found that each of the exchanges have contributed to price discovery.

Malkamäki et al. (1991) have analysed the co-movements of stock returns in 24 countries during 1988. Malkamäki et al. (1991) have presented evidence which clarify the segmentation of financial markets. Firstly, he has found certain risk categories in the stock markets. Potential reasons for the existence for these categories can be currency areas and economic trade. These categories have seemed to affect the riskiness of the different stock markets, e.g. North American, European, and Ocean stock exchanges quite clearly have created their own separate factors. Second statement has based on the level of institutional development which determine the level of international capital co-movements. Thirdly, the thinly traded stock markets, such as Finland, have seemed to exhibit price behaviour of their own. To be more confident of the role of the international capital movements to the Finnish markets, some evidence from the Finnish basis is needed, indeed. The following section presents some results of the international capital movements with respect to the Finnish financial markets.

4.2. The Finnish Arena

The first paper of the Finnish stock price co-movements with respect to global markets has been spelt out by Hietala (1989). He (1989) has reported that *individual* stock prices are not dependent on the behaviour of foreign, more exactly, on the US stock markets´ behaviour. But, there is indeed a need for up-dating Hietala`s arguments, just on account of the recent development of financial markets, and especially the considerable changes in Nokia Corporation.

The research of Berglund and Liljeblom (1990) has carried out how two important changes in the Finnish stock markets have affected stock price volatility on the Helsinki Stock Exchange. These changes are enormous increase in trading volume and a sudden increase in the interest of the Finnish stocks shown by foreign investors in the beginning of the eighties. The results obtained by Berglund and Liljeblom (1990) have submitted that the internationalisation of the Finnish stock markets is more important single factor in explaining the observed changes of stock prices volatility during the eighties than the increase in trading volume.

Although the increased trading volume and the increase in the foreign interest of the Finnish stocks are to some extent linked each other, it has been shown by Berglund and Liljeblom (1990) that these phenomena are expected to have diverse effects on the volatility. One explanations of the remarkable increased trading volume has been the dramatically increased interest of international investors for the Finnish stocks during the period 1987-1988. (Berglund and Liljeblom, 1990)

Berglund and Liljeblom (1990) have observed a significant increase in the volatility when moving from the low-turnover to the high turnover period. This has been the case even after making some adjustments in serial correlation structure and omitting the crash week effect in 1987. The higher volatility have been - at least partly - explained by foreign trading in the Finnish stock markets. Therefore, there have been some factors that seem to have exaggerated the increase in the stock price volatility in the Finnish stock markets. Berglund and Liljeblom (1990) have suggested that the change in the autocorrelation pattern between the different volatility periods is the most important of these factors. Additionally, the higher volatility observed in individual stock has also been present in the market returns[15], the higher return has been interpreted as a higher risk premium due to the higher volatility (Berglund and Liljeblom, 1990)

In accordance with the findings of Malkamäki et al. (1991), Martikainen and Puttonen (1991) have shown that the global returns do not seem to produce significant information to the Finnish stock markets. (Malkamäki et al., 1991; and Martikainen and Puttonen, 1991) Martikainen and Puttonen (1991) have gone through a Granger-causality investigation of informational flow from the world`s stock markets to the thin Finnish stock and stock index futures markets. They have not observed any causal relation between the returns of world-wide and the Finnish stock markets.

Martikainen et al. (1991) have illustrated clear evidence of a market segmentation. According to the findings of Martikainen et al. (1991), the Finnish stock market are segmented of the Swedish and the U.S stock market. It has been revealed by Martikainen et al. (1991) that several the Finnish stocks include significant Swedish risk components, while the interrelation between the Finnish and the U.S. markets has been found considerable lower. Malkamäki et al. (1991) have presented evidence of differently behaved returns on the thinly traded stock markets with respect to the major stock indexes. Additionally, Mathur and Subrahnamyam (1991) have found the different returns behaviour of the Finnish stock markets with respect to the other Scandinavian markets.

More Scandinavian evidence between volatility information flow has been reported for example by Pynnönen et al. (1994). They have found out by using a ARMA-GARCH - model that volatility lead-lag transmissions between Finland and Sweden are strongly time dependent. The Scandinavian markets have shared common time lags in volatility shocks but the lag structure has became shorter in the course of time. (Pynnönen et al., 1994).

Booth et al. (1995) on the one hand have not found any causal relationship between the US and the Finnish cash market. On the other hand, they have reported a significant predictive power of the US markets on the Finnish futures returns. Geoffry et al. (1995) have studied stock price volatility spillovers in Scandinavian stock markets using a Exponential Generalised Autoregressive Conditional Heteroscedasticity (EGARCH) model. Their results have revealed that the transmission of the volatility has been asymmetric and the spillovers have been more pronounced for the bad news than for the good ones. Further, they have suggested that the markets do not share the same volatility process and are not cointegrated in the long-run. In spite of the high level of similarities between the markets, the volatility spillovers have remained relatively low, however in some cases statistically significant. In this context, as Geoffry et al. (1995) have concluded global financial market are not so informationally integrated as one may might think at first glance.

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[15] In other words, to the extent that the increased volatility is explained by an increase in the market risk rather that an increase in unique risk of the firm (Berglund and Liljeblom, 1990, p. 10).

The very latest study of macroeconomical variables and stock market volatility with the Finnish data had been carried out Liljeblom and Stenius (1997). According to their results, the between one-sixth to above two-thirds of the changes in the stock volatility can be explained by the macroeconomic volatilities. These findings are much stronger than the correspondent results on the US basis.

It has been proposed in media that the actions of foreign investors may increase volatility in the Finnish stock markets. Martikainen (1994a) has agreed this statement, but the role of the foreign investors is two-side coin: on the one hand, the foreign investors can indeed increase the volatility by rebalancing their portfolios which typically means selling or buying extensive amounts of stocks, and hence cause greater volatility. But on the other hand, the foreign investors´ inputs are needed in order to obtain liquidity and active trading in the national stock markets. Moreover, the national investors should also react similar way as the foreign ones, if the future of domestic positions are no longer promising. The Finnish investors, however, probably rebalance their positions with the other Finnish assets if their investment policy, preferences or investment research capacities etc. somehow restrict investments abroad. Thus, the presence of the foreign investors in the national markets should not be seen as a threat, rather the possibility for better conditions of trading.

The very recent evidence of the capital co-movements on the separate stock markets is the research by Hedvall et al. (1997). Hedvall et al. (1997) have studied the Nokia´s price discoveries in NYSE and HeSE and the effect of the NYSE listing. According to their results, the variations of the HeSE returns have been clearly more driven by trading on the NYSE than vice versa. In particular, the past HeSE returns have seemed to enter with a negative coefficient, which supports the existence of mean-reversion or ”temporary” price effects on HeSE (Hedvall et al., 1997, p. 17).

It is essential to note that the previous results of analysis of dual listed companies are somewhat incomprehensive. There is clear evidence of negative effects on dual listings, but there is also support for positive or insignificant effect of listings abroad. Due to different approaches to measure the effects of dual or grater listings in foreign stock exchanges, more detailed description of previous studies is not done. Hedvall et al. (1997) have presented a review of the recent studies and the dual listing effects in volatilities and trading volumes.

It is useful to recognise the role of market microstructure in Helsinki and its relevance to New York. Comparison of the typical properties between the stock exchanges should be essential in understanding the basic differences of these market places. These aspects are handled in the following section.

4.3. The Market Microstructure of Helsinki Stock Exchange

The Finnish stock markets may suffer from a shortage of good-quality, large-capitalisation shares, which may result in rapid overheating when the domestic and international interest has been stimulated by market liberalisation, structural changes etc. There is also some evidence of closing price manipulation on HeSE (Felixson and Pelli, 1997). The President of the Helsinki Stock Exchange Juhani Erma has stated, the biggest problem is the lack of the Finnish long-term dividend-interested investors (http://www.kauppalehti.fi). One problem may be the sudden mobility of foreign institutional investors which results to higher price volatility in the Finnish stock markets. This concerns especially Nokia Corporation because the foreign investors are the biggest ownergroup of Nokia Corporation (http://www.kauppalehti.fi). It has been suspected by many journalists, financial economist and investors that the collapse in share prices of Nokia in 9.5.1996 was due to the foreign institutional investors´ co-sellings[16]. Additionally, it has been speculated that do institutional investors with enormous capitals have too strong influence on Nokia´s share price movements and hence a possibility to influence (due to strong weight of Nokia Corporation in HEX-index) on the Finnish financial markets as a whole (http://www.kauppalehti.fi).

The NYSE is the biggest stock exchange in the world and the HeSE is regarded usually as a thinly traded market place. Some of the observed differences of volatility information flows between the markets can be explained by that the markets are open for transactions only for very short overlapping time during the trading days. The results of applied analysis will be interesting since the Helsinki Stock Exchange closes after 30 minutes when the NYSE has opened for trading. However, due to the different trading mechanism between the exchanges, *the free trading*[17] on the HeSE take places from 10:30 a.m. to 5:00 p.m. in Finnish time and the NYSE is opening at the same time 5:00 p.m. in Finnish time. Additionally, the changes in summer time vary overlapping trading hours between the HeSE and the NYSE. (For exact information of trading hours, national and religious holidays and days of interrupted trading, see http://www.hex.fi and http://www.nyse.com.)

The Finnish stock markets and especially the most liquid stock in HeSE, Nokia Corporation, offer an interesting arena for the investigation of relationship between stock prices volatilities and trading volumes in two, illiquid and liquid stock markets. The interesting arena can be justified also by the facts that the Helsinki Stock Exchange has different trading mechanism than the correspondent in the NYSE. But this aspect might also be a problem in comparisons between the stock markets, hence the trading mechanism in the HeSE, the *calling out* mechanism[18], has led to increased time-series dependence in return series. (Berglund and Liljeblom, 1988)

Furthermore, the trading in Finnish stock market has considered infrequent, which leads to slower price adjustments of infrequently traded stocks. But in the case Nokia Corporation, the trading is the most frequent among the traded stocks in HeSE. In this context the

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[16] It has been revealed that the one of the main reasons for the collapse in Nokia`s share prices in the autumn 1995 was due to selling actions by the biggest US fund, Fidelity. (http://www.kauppalehti.fi)

[17] Trading day in HeSE can be divided into three time periods; *pre-trading* (9:30 a.m. - 10:30 a.m. and *matching* (10:20 a.m. - 10:30 a.m.); the second period, *free trading* (10:30 - 5:00 p.m.); and the third period of the trading day is *closing quotations* (5:00 p.m.) and *after market trading I* (5:05p.m. - 6:00 p.m.). *After market trading II* takes places on the following trading day at 9:00 - 9:25 a.m. (http: //www.hex.fi)

[18] Trading in each stock has started with "calling out" where only a part of the traders for the day were executed, while the rest of the traders have occurred in the "aftermarket", where the trading prices were limited by the highest and lowest as at the end of the calling out. Among the previous studies, this mechanism has led *additional* serial correlation in stock returns. (e.g. Martikainen et al. 1994, and Berglund and Liljeblom 1988). For more detail description and market microstructure evaluation of HeSE trading mechanism, see *inter alia* Hedvall (1994), Helsinki Stock Exchange (1997b,1996), http: //www.hex.fi, and of NYSE, http://www.nyse.com.

infrequent trading effect will be the smallest in the Finnish stock markets. It has been argued by not only by investors, but also by the authorities of financial markets and academic researchers, that the influence of Nokia in HEX index biases the picture of the Finnish stock markets as whole.

Short selling restrictions may also decay price adjustment process in the Finnish stocks since there are no institutional framework for selling stocks short on the HeSE. Different institutional trading places for stocks and option markets may play informational role in price process adjustments in Finland since investors can take short positions in forward markets. The restrictions for foreign investors have been decreased during the nineties. These aspects may have had influence on the volatility and volume behaviour and then on the relationship between these variables. Hence, these factors may have decreased the generalisation of earlier empirical results of Finnish market. More detail descriptions of the liberalisation, the deregulation and the recent development of the Finnish and the American stock markets are reviewed in Helsinki Stock Exchange (1997b, 1996), http://www.hex.fi and http://www.nyse.com.

In spite of great evidence of international capital movements across national stock markets, the role of new information arrival must be evaluated more deeply. News affect not only to volatility but also to trading volume, so in this context this phenomena must be discussed. This is done in the following sections.

5. NEW INFORMATION ARRIVALS: REACTIONS OF VOLATILITY AND VOLUME

5.1. Trading Activity with Respect to New Information

Webb (1994) has put considerable attention to macroeconomic information with respect to financial trading activity. Webb (1994) has emphasised that prices may perform *one or more roles* with respect to information production and dissemination process. First, the prices may be source of information to especially uninformed investors. Secondly, the prices are considered as an aggregate information across investors.

Turbulent periods that follow press releases are often preceded by relatively peaceful periods as trading activity declines in advance of the release of new information. This means that recurrent patterns in the volatility of speculative prices should be observable around the release of new information. Engle, Ito and Lin (1990) have stated that observed clusters in the volatility of speculative prices must lie either in the arrival process of news or in market dynamics in response to new information. Presumably, the larger the consensus forecast errors are within investors, the greater the response in prices will be. An alternative hypothesis is that these financial releases contain what Black (1986) calls *noise*. Shortly said, noise is non-informational factors to which speculative prices react rather than the real information.

It is possible to formulate market´s forecast error which is the difference between observed and forecast after the information releases. The reaction of speculative prices to new information, however, depends not only on the size of the forecast errors but also on the beliefs (about relationship of fundamentals) that traders use to interpret the data. (Webb, 1994, p. 2)

However, the reaction to the new information is often fairly puzzling and a number of questions naturally arise. Webb (1994) has put four different aspects of the varying reaction to the new information. Firstly, the interpretation to a given piece of information sometimes have changed radically over time. Secondly, same news releases are periodically extremely important and at other times virtually ignored by market participants even though large forecast erros exist in both cases. The market´s perception of what constitutes an important number changes over time. Thirdly, the focus of the market participants is constantly shifting. The deeper interest is keen on to the "sexy" corporations and industries. The latest point which may affect uncertainty into prices are the false conceptions of the relationship between economical fundamentals.

All together, forecast errors, incorrect opinions of the market dynamics of the economical fundamentals and simultaneously arrival of other information may explain the apparent anomalous reaction of stock prices. Certainly, the observations of apparent anomalies in speculative prices do not necessarily indicate that market participants are necessarily irrational; unexploited profit opportunities exist; or that anything goes. (Webb, 1994) As Merton has concluded (1987):

> ... financial markets dominated by rational agents may nevertheless produce anomalous behaviour relative to the perfect market model. Institutional complexities

> and information costs may cause considerable variation in the time series over which different types of anomalies are expected to be eliminated in the marketplaces. (p. 508)

Price reaction connected to news releases may be also less rational. Usually, the concepts of *overreaction* is referred when the market´s participants have reacted "too much" with respect to the new information which is can be seen as a significant volatility storms and high trading volume periods. The strong reaction of the prices indicates *informational content* of the news releases and the inferior forecast ability of the market participants. The motives of the strong reactions may be wrong or spurious. Additionally, the reaction behaviour may include noise. (Webb, 1994, p. 19-20)

Uncertainty and information are linked with each other. Uncertainty reflects lack of information. Changes in stock prices in the future are uncertain because there is *incomplete information*. Much of the variation in speculative prices is attributable to the flow of new information. There is vast amount of the relevant information concerning the underlying assets in financial markets and then available information frequently differs across individuals. Black (1986) has argued that a *necessary* condition for trading is the existence of differences in information across the market participants. An alternative approach is that trading may occur even when individuals share the same information if the market participants interpret the same information differently. As Webb (1994) has put:

> "the differences in opinions not only make horse race possible but also account for much of the activity on financial markets. (p. 30)

However, the manner by which the new information enters the market place and how it is incorporated into security prices is not well understood at present (Webb, 1994, p. 30). To be more convinced about the role of the new information to the assets prices, the concept of informationally efficient market is essential to present.

5.2. Informationally Efficient Markets

The concept of informationally efficient markets suggests that security prices change only in response to the arrival of new information. Consequently, changes in speculative prices reflect the flow of new information in financial markets. The informational efficiency is used in discussions concerned with the relationship between market prices and information[19]. Fama (1970, 1976) has used terms "efficient capital markets" and "market efficiency". Beaver (1981a, 1981b) also has referred to "market efficiency". Jensen and Smith (1985) have referred to "efficient market theory" in the connection with the idea that prices reflect information. Merton (1985) has introduced "rational market hypothesis" to refer the relationship between market prices and information. Jensen (1978) has defined an informationally efficient capital markets as a markets in which it is not possible to earn a "pure" or "economic" profit based on a given and presumably shared information set. Thus, the informationally efficient capital market is simply a market in which speculative

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[19] It is important to distinguish the *allocative efficiency* and *informational efficiency*. However, as noted by Strong and Walker (1987), the precise relationship between these two concepts is not clear.

prices do not *systematically* deviate from the prices the securities would be expected to command given available information commonly shared by the rational investors.

Robert (1959) has divided informational efficiency into three types: weak from, strong form, and semistrong form[20]. Fama (1970) has defined an informationally efficient capital markets as one in which speculative prices fully and correctly reflect all available information. An extensive evaluation of the informational efficiency of financial markets has been provided by Strong and Walker (1987).

Changes in speculative prices in the efficient markets occur only in response to new information or reassessments of existing information. Prices adjust to new information immediately and without any intervening price equilibria. According to Webb (1994) the *sufficient* conditions for efficient markets are i) zero transaction cost and taxes; ii) zero information production and dissemination costs; iii) complete agreement among investors regarding the future distribution of security returns. The informational efficiency may still exist, however, even in a world often characterised by the imperfections. The conditions mentioned above are *sufficient, but not necessary* for the market efficiency (Webb, 1994, p. 34). Additionally, there is a concept of *over informationally efficient* market, developed by Grossman (1975). The markets which are over efficient reflects excess information. Prices include too much and also useless information which can be called *noise*.

If financial markets are informationally efficient one would not expect to observe causal relationships between changes in volume and changes in security prices at all. Wood et al. (1985), Amihud and Mendleson (1987) and Stoll and Whakey (1990) have reported U-shaped patterns in the volatility of stock returns during trading day. Webb and Smith (1994) have reported similar evidence of U-shaped volatility for the Eurodollar futures prices on the Chicago Mercantile Exchange (CME). Webb and Smith (1994) have contended that the various volatility measures employed are *information* dependent rather than *volume* or *time* dependent. Simply stated, the arrival of new information is the driving force behind the influence of trading activity on price changes and *not* volume *per se*. Further evidence can be found in Clark's (1973) classic *Econometrica* article where he has stated

> On days when no new information is available, trading is slow, and the price process evolves slowly. On days when new information violates old expectations, trading is brisk, and the price process evolves much faster... When new information flows to the market, both prices and traders' price expectations will change. If the information is uncertain (i.e., some traders shift expectations up and others down on the basis of the information), or if only "inside" traders get the information first, then large price changes will be coincident with high volumes. (p. 137-145)

Information can be regarded as a good so there is also markets for information. Information production is costly and dissemination of information include also elements of uncertainty.

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[20] The weak form of the market efficiency posits that the sequence of the previous price changes do not contain any relevant information about the future price changes. The semi strong form market efficiency assumes that market is efficient only with respect to all public information. Inside information possessed by investors could be profitably exploited in a capital market that is only semi strong efficient. The strong form posits the markets is efficient with respect to all available information also unpublished information.

Grossman and Stiglitz (1976) have emphasised that if information is not free of charge, markets can not be informationally efficient. Individual investors have no economical incentives to produce information if markets already reflect all relevant information. But, if no one produces such a information, then the market cannot reflect all available relevant information and hence can not be efficient.

Although markets may arise from the non-informational factors such as a sudden increase in trading volume (due perhaps to triggering a number of large stop-loss orders or other similar auto-determined investing strategies) or as the result of a spillover of sharp changes in other close related security prices, say, due to a crash, most markets arise from the release of new information.

There is constantly growing evidence that the capital market may not be informationally efficient and that speculative price change in response to both the arrival of new information and traders´ reactions to noise, that is non-informational factors and fundamentals. French and Roll (1986) have reported significantly greater volatility during the trading than the overnight. This is a surprising result if one believes that new information arrives evenly throughout the full day. French and Roll (1986) have explained the differential volatility primary to traders acting on private information, mispricings by traders and traders acting on public information. Their results has been regarded parallel with the concept of *noise trading*[21]. Moreover, there is significant amount of evidence that the changes in speculative prices are too volatile to be accounted for by the changes in information on the fundamentals alone. This is consistent especially in stock markets basis. Evidence for this "excessive volatility" with respect to the fundamentals can be found e.g. in Shiller (1981a, 1981b, 1989), LeRoy and Porter (1981), and DeLong and Bect (1992).

5.3. Fundamentals versus Noise

Financial research has also pointed out some shortcomings with respect to the fundamentals´ role in determing market volatility. For example, Liljeblom and Stenius (1997) have concluded that the explanatory power of fundamentals might be rather low in explaining stock market volatility. Roll (1988) has reported that only a third of the monthly variation in individual stock returns can be explained by macroeconomical variables.

There are several suggestions why efficiency tests failure to accept informational efficient market hypothesis. One reason for standing inefficiency is according to Modigliani and Miller (1979) *the money illusion* with respect to discount rate. Summers (1986) has provided evidence of the low power of the efficiency tests. Additionally, it has been questioned can efficiency tests be modelled with linear modifications. (Meese and Rose, 1990)

[21] The noise trading models have regarded as somewhat controversial and very difficult to test empirically. But, they can explain to some extent why speculative prices react at certain way during the news arrivals. For more discussion of noise in financial markets, see e.g. Shleifer and Summers (1990).

According to Frankel and Froot (1990) much observed large trading is based on noise rather than news, and leads to excessive volatility. Meese (1986) has recognised the potential influence of noise on changes of speculative prices:

> While many economists believe that asset prices reflect the values of the underlying market fundamentals, asset market participants often express the view that fundamentals are just part of the story. Chraracteristisations of asset price movements from the latter group often include discussions of "extraneous events"... (p. 369)

According to Black (1986) the existence of noise trading is a necessary condition for active, liquid financial markets. Black´s (1986) analysis has implicated that noise trading will cause "excessive volatility" in the short run. More noise trading in markets, the greater is the potential departure from intrinsic value and the greater the volatility of speculative prices.

6. DATA DESCRIPTION

6.1. The Special Properties of Nokia Corporation

Some preliminary research concerning stock price behaviour of Nokia Corporation on the HeSE has been carried out by Sorjonen (1995, 1996)[22]. Parallel to the numerous articles of the Finnish media, it has been shown by Sorjonen (1995, 1996), that the common stock Nokia A is more liquid stock than the preferred stock Nokia K on the Helsinki Stock Exchange. Better liquidity can be explained by lower election voice power premium, because Nokia K has ten times greater voice power compared to Nokia A (http: //www.nokia.com). However, dividend policy is the same for both of the shares in monetary context [23].

Sorjonen (1995) has emphasised that the premium concerning voting power in shareholders´ meetings has been vanishing in the course of time: it can be expected that the more voice powered stock, the common Nokia K, should be more expensive than the preferred Nokia A. The situation is different in the case of Nokia Corporation: the election power premium has been negative. Negative premium indicates that investors have been more interested in the liquid stock Nokia A. The negative premium may be due to the ownership of foreign investors, because typically they are interested more in returns of underlying stocks than the operational management of the underlying company.

Sorjonen (1995), among many others, has shown that there is a tendency for chancing the common Nokia K stocks to the lower voice powered Nokia A. Portfolio rebalancing which indicate position changes from the preferred Nokia K to the common Nokia A, may be due to Nokia´s aim to give up with trading of the more illiquid stock Nokia K on the HeSE (http://www.kauppalehti.fi)[24]. These findings give proper reasons to concentrate on one stock serie on the HeSE, that is Nokia A, and compare its dependencies on the NYSE traded ADS stock serie in order to set a proper relationship between trading volumes and volatilities.

6.2. The Role of Exchange Rates and Time Spans

The series are originally measured as local currencies, that is the prices of Nokia A are measured in FIM and Nokia ADS in USD. But the issue of different currency based stock prices can not be neglected. Stock prices on the HeSE may be influenced on the behaviour of the US dollar. For example, the investment bank Merrill Lynch, among many others, has called attention to the revaluation of USD which very probably increases the selling volume of Nokia Corporation. Other currency influences on stock prices are minor because the contracts made by Nokia and its customers are typically on USD basis.

[22] The papers have been presented in the seminars in business economics 26.10.1995 and in statistics 12.4.1996 at University of Joensuu, Finland. The papers can be obtained by request from the author.

[23] Dividend per share for both stocks Nokia A and Nokia ADS has been 2.50, 3.00, and 3.50 FIM in 1994, 1995, 1996 respectively. One ADS equals one A stock. (Nokia Corporation, 1996)

[24] Nowadays, stock holders have an opportunity to change their positions from Nokia K to Nokia A. On the Helsinki Stock Exchange in May 14. 1997, the number of A stocks was 208 853 746 of total 299 549 980, approximately 70 per cent of the total number of the shares of Nokia Corporation (http://www.hex.fi).

(http://www.kauppalehti.fi). If the perspective is of the local investors point of view, currency conversion need not to carry out. In such a situation, the changes in time series of the interest reflect how the local market reacts to information from foreign markets. (Eu and Shim 1989, von Furstenberg and Jeon 1989, and Choudry 1994, Hedvall, 1997) But on these above mentioned grounds, exchange rate fluctuations of the data have to be eliminated. All Helsinki based stock price series (the highest, lowest and closing prices of the trading day) have been converted to USD base in terms of avoiding exchange rate changes and making volatility series to the same scale. This conversion has been done by using USD/FIM spot fixing, calculated by the Bank of Finland.

In order to analyse the long-run or structural changes or other instabilities within estimated parameters, the data was split into two subperiods. Thus, using three different time spans it is possible to be more confident of the robustness and instabilities of the results. The observation period covers 537 daily observation from 20.7.1994 to 9.8.1996. The first subperiod covers the observations 1 to 268 and the second subperiod observations from 269 to 537.

6.3. The Measurement Issues of Volatility

6.3.1. Volatility Measures

One main problem is how to describe properly stock price volatility[25]. The term "price change or volatility" is usually associated with the concept of price change relatives, which is normally computed as the first differences in the log price or the percentage price change (Karpoff, 1987, p. 110). There exist several approaches for estimating the unobservable volatility as a concept of price uncertainty, risk or lack of information.

Most volatility measures are based on the closing quoted values of indexes or asset prices. Different measures of return volatility can be found, for example Sharma et al.,1996; Holmes, 1996; Martikainen et al., 1994; LeBaron, 1993; and Ragunathan and Peker, 1996. The main differences between calculation procedures are different transformations (logarithms, squared, squared root, etc.) and dividend notation of indices or assets prices. The calculation procedures of the daily prices have varied among studies: a representative daily price of asset is calculated as an average of low and high prices of the trading day, or some studies have used just closing prices or open and closing price ratios. The geographical aspect of research has also influenced the return calculation procedure: returns are measured with different exchange rates, but the returns are transformed into same currency when focus has been global to avoid exchange fluctuations. Unfortunately, some studies have ignored exchange rate movements and hence time series have been measured at local currencies.

A more sophisticated method for returns has been carried out e.g. by Berglund and Liljeblom (1990) who have adjusted returns due to serial autocorrelation structures. Some

[25] There is extensive literature which handles the concept of volatility in financial markets. For example, Shiller (1989) and Brailsford (1994b) have carried out extensive review essays of previous volatility studies. More recently, Rossi (1996) has reviewed several studies on the recent development of modelling volatility.

studies (e.g. Pursiainen and Viitanen (1996) have taken into account market returns for obtaining abnormal returns of assets of the interest. Day and Lewis (1992), among many others, have noted also risk free market return. Evaluation of different volatility estimators has been carried out by Bern (1994).

To overcome such complicated and varying calculation procedures, this paper takes a little bit different view to volatility, that is *the intraday approach*. This will give interesting results in the forthcoming analysis. The research carried out by Chatrath et al. (1995) has distinguished *intra- and interday* volatilities from each other. Chatrath et al. (1995) have not only used relative volatility measures, but also investigated absolute values of return volatilities. Intraday volatility has been measured as

$$VOLATILITY_t = \left(\frac{(p^{high} - p^{low})_t}{p_t^{mean}} \right) \tag{1}$$

where p^{low}, p^{high} and p^{mean} are the lowest, highest and mean quoted price of the day t, respectively. The second "interesting" volatility measures has been applied e.g. by Herbert (1995) in his analysis of trading volume, maturity and natural gas futures price volatility. The volatility has been measured as

$$VOLATILITY_t = \frac{[\ln(p^{high}) - \ln(p^{low})]_t^2}{4\ln 2} \tag{2}$$

where p^{low} and p^{high} are the lowest and highest quoted price of the day t and *4ln2* is a scaling operator. The third "interesting" volatility measure, used e.g. in the work of Tscoegl (1982), is the following:

$$VOLATILITY_t = 0.5(\ln p_t^{high} - \ln p_t^{low})^2 - (2\ln 2 - 1)(\ln p_t^{close} - \ln p_t^{open})^2 \tag{3}$$

where p^{high}, p^{low} and p^{close} are the highest, lowest and closing quoted price of the day t, respectively.

However, the problem is choosing which measure to choose for the later analysis. The second volatility measure is somewhat confusing with its nominator: explanation for this scalar is unclear. The third measure can not be applied because of the different trading mechanism between HeSE and NYSE. Closing and open prices are not applicable since in HeSE "the calling-out" and after-market periods may not indicate properly the real price formulation of the market compared to "the free trading" period. There is also evidence on Finnish stock markets evidence of closing price manipulation (Felixson and Pelli, 1997). Furthermore, if the logarithms of p^{high} and p^{low} are the same on the same trading day some serious problems are present.

6.3.2. The Choice of Volatility Measure

The use of explicit standard deviation as in French et al. (1987) or Schwert (1989) would lead to a higher level of time aggregation and hence does not support the purpose of this study. Furthermore, if the return series are slightly trended and autocorrelated and therefore in some sense predictable, standard deviation as a measure of volatility would not be an appropriate measure of risk. (Pynnönen et al. 1994)

Statements mentioned above have forced concentration on the first volatility measure, with small modification. The modification has been done by *replacing the mean of quoted stock price of the trading day with the quoted closing price*. This modification can be argued by the fact that the closing price pictures trading better than the mean of the prices of the day, because bias in the mean can be influenced by e.g. a single very high or low stock price. It is a well-known fact that closing prices describe the information flow of the trading day and hence set out what has been really happening during the day. The intraday volatility used in this analysis is obtained by the formula

$$VOLATILITY_t = \left(\frac{(p^{high} - p^{low})_t}{p_t^{close}} \right), \tag{4}$$

where p^{high}, p^{low}, p^{close} are the highest, lowest and closing quoted price of the trading day, respectively. The chosen volatility measure is based on the *ad hoc basis* because the focus of this research is not based on evaluating different volatility measures. This volatility measure has been developed to fit this study, because the availability of the quoted highest, lowest and closing prices and trading volume series of two stock markets at a very reasonable expense. The highest and lowest stock prices of the trading day can reveal important released information about economy, industry or Nokia itself. In this context this "new" volatility measure has to be considered a valuable indicator of the intraday volatility.

6.3.3. The Descriptive Statistics of Volatility Series

Basic descriptive statistics and qualitative interpretations of the intraday volatility and trading volume series are presented in this subchapter in order to learn some basic properties of the volatility and volume series. Some basic diagnostic statistics of intraday volatilities of Nokia A and Nokia ADS (hereafter referred to as VOLAA and VOLAADS, respectively) are presented in Table 1. below. Figures 1. and 2. present time sequence plots of volatility series on the same scale.

Table 1. Descriptive statistics. Intraday volatility series of Nokia A and Nokia ADS.

Descriptive Statistics	*VOLAA*	*VOLAADS*
Mean	0.024420	0.025065
Median	0.020534	0.020979
Maximum	0.208383	0.112360
Minimum	0.003008	0.003436
Standard Deviation	0.018994	0.016371
Skewness	3.953909	1.569562
Kurtosis	28.53282	6.326042
Jargue-Bera (Prob.)	15956.24 (0.000000)	467.1385 (0.000000)
Observation period	20.7.1994-9.8.1996	20.7.1994-9.8.1996
Sample size	537	537

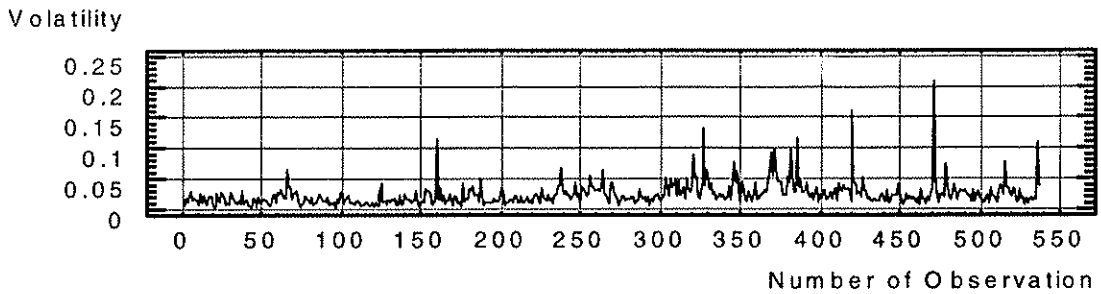

Figure 1. Time sequence plot. Intraday volatility of Nokia A.

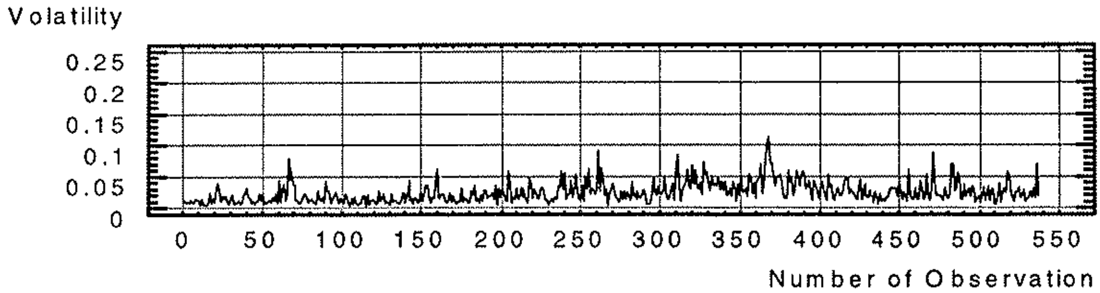

Figure 2. Time sequence plot. Intraday volatility of Nokia ADS.

Diagnostic checking has not revealed considerable differences between the share series, since standard deviations are very near to each other. Standard deviation of VOLAA is 0.018994 and for VOLAADS 0.016371. The greater sensitivity to new relevant information on the Finnish stock market can be argued by the higher level of standard deviation of VOLAA compared to VOLAADS. On the grounds of standard deviation of the volatility series, it seems that the HeSE reacts more quickly than the NYSE to new relevant information. This somewhat "confusing" result might be due to the fact that when Nokia Corporation releases new information during the HeSE trading, the NYSE is still closed[26]. In this respect, re-evaluation of "right" stock price caused by the news effect, is incorporated when the NYSE opens.

The mean of the volatility series of Nokia A and ADS have indicated that average volatilities, 0.024420 and 0.025065 respectively, are fairly similar between stock exchanges. The most remarkable difference in descriptive statistics is maximum values of volatility series: The volatility of Nokia A has an almost twice greater single intraday volatility value than the corresponding value of Nokia ADS (0.208383 and 0.112360, respectively).

Parallel to the previous studies, volatility processes are not normally distributed. As it can be seen from Table 1. the departure of normality is larger with VOLAA, but neither is VOLAADS serie normally distributed. The Jargue-Bera test[27] rejects the null hypothesis of

[26] For more discussion of news releases of dual listed companies and the concept of time difference between markets, see e.g. Hedvall (1997).

[27] The Jargue-Bera statistics test weather a serie is normally distributed. The test statistic depend on skewness and kurtosis of a serie. Skewness is a measure of symmetry of distribution. Symmetrical distribution, such as normal distribution, has zero skewness. Kurtosis is a measure of thickness of tails of the distribution. The kurtosis of a normal distribution is 3. Under the null hypothesis of normal distribution, the Jargue-Bera test is distributed as chi-squared with 2 degrees of freedom. (e.g. MicroTSP online)

normality in both volatility series with all commonly used significance. More precisely, the skewness for both series is positive, even if VOLAA indicates very positive skewness (3.953909) compared to VOLAADS (1.569562). Kurtosis indicates that the tails of the distributions of both volatility series are thicker than with normal distribution (Nokia A 28.53282 and Nokia ADS 6.326042). Especially the intraday volatility series of Nokia A indicates very thick tails which may be caused by a few clear abnormal observation in the data.

Because the study also accounts for trading volume series, similar descriptive statistics and time sequence plots have been applied in order to state similar/different behaviour in trading volume series. This is done in the following section.

6.4. The Measurement Issues of Trading Volume

6.4.1. Trading Volume Measures

Financial markets have been found to be most active at the beginning and end of the trading day (Hedvall, 1994, p. 48). In the context of volume series, Ajinkya and Jain (1989) have emphasised that autocorrelation in trading volume may be large because all traders do not trade within one day on the information they use to rebalance their portfolios. Some investors could adjust their portfolios later than others either because they come to know the new information later or they choose to trade only periodically to minimise direct and indirect transaction costs.

The "right" choice of the proper measure for the trading volume series is a simpler task than with the concept of the volatility series. Hedvall (1994) has stated it "volume is a priori more attractive measure of activity than number of transactions" (p. 93). The trading volume series consists of the number of stocks traded during the day. Trading volume series of Nokia A and Nokia ADS (TRADEA and TRADEADS, respectively) are measured as the logarithm of the trading volume per day. Instead of using an absolute series of trading volume, it has been suggested to measure volumes by their relative changes. Relative change transformations can be justified e.g. in order to avoid the heteroscedasticity problem. Ajinkya and Jain (1989) have investigated the effects of alternative transformations on volume distribution. Among their findings, a natural logarithm transformation of the number of share units traded appears to be a suitable procedure. Transformations to USD basis are not needed for trading volumes because the logarithm transformation gives the relative change of each trading volume series.

6.4.2. The Descriptive Statistics of Trading Volume Series

It should be clear on *an a priori basis* that *absolute* trading volume in NYSE is greater than in HeSE. Considerable differences between absolute trading volumes suggest using the relative changes of trading volume series. The changes will be better descriptions not only on the intraday basis, but also based on the time span as whole the trading volume frequencies. Basic diagnostic statistics of trading volumes of Nokia A and Nokia ADS are presented in Table 2 below. Figures 3. and 4. below present the time sequence plots of the trading volume series.

Table 2. Descriptive statistics. Trading volume series (in logs) of Nokia A and Nokia ADS.

Descriptive Statistics	*TRADEA*	*TRADEADS*
Mean	6.049724	6.459959
Median	6.102071	6.453152
Maximum	8.560748	9.399969
Minimum	3.618886	3.858622
Standard Deviation	0.664912	0.869548
Skewness	0.005697	0.379272
Kurtosis	4.148712	4.141890
Jargue-Bera (Prob.)	29.47259 (0.00000)	41.97105 (0.00000)
Observation Period	20.7.1994-9.8.1996	20.7.1994-9.8.1996
Sample Size	537	537

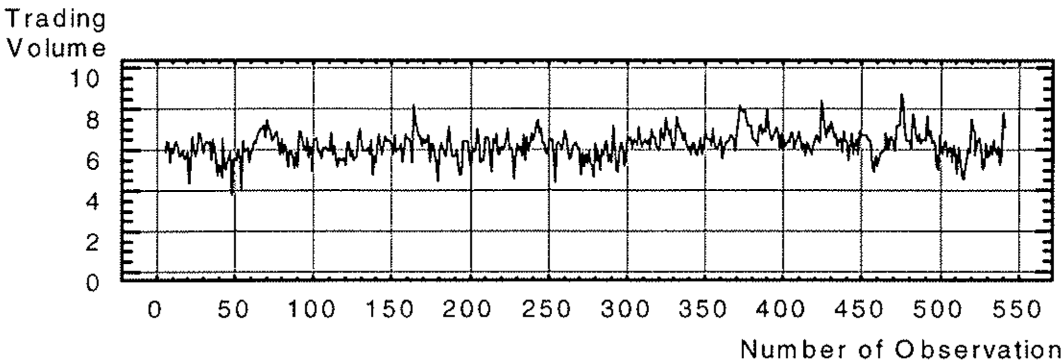

Figure 3. Time sequence plot. Trading volume of Nokia A (in logs).

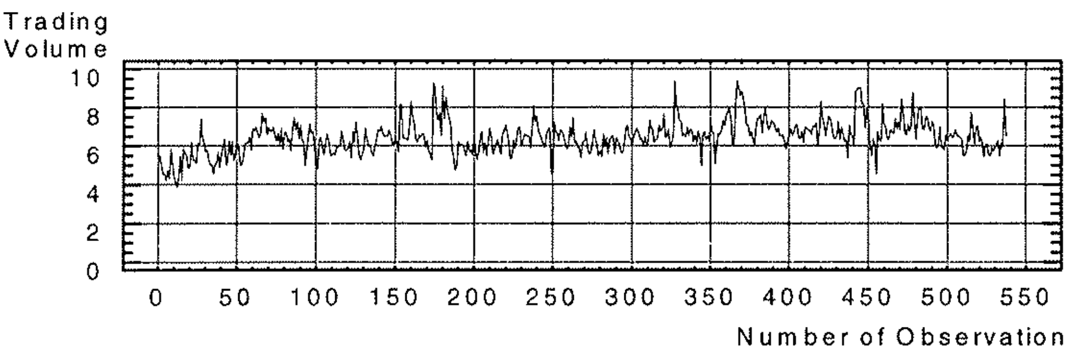

Figure 4. Time sequence plot. Trading volume of Nokia ADS (in logs).

Similar behaviour between the trading volume series is fairly considerable; the mean, minimum and maximum values of the series indicate that the average and the extreme values do not vary considerably within volume series. Standard deviation of volume changes are quite near to each other, Nokia A with 0.664912 and Nokia ADS with 0.869548. These findings suggest that fairly similar trading behaviour changes between stock exchanges even if the absolute total turnover of the stock exchanges is remarkable.

The figures of skewness and kurtosis of volume series clearly have smaller magnitude than in the context of volatility series. However, the Jargue-Bera test rejects the null hypothesis of the normality in both of the series with zero probability values. The kurtosis of TRADEA and TRADEADS are similar, 4.148712 and 4.141890 respectively, but the volume of Nokia ADS is more greatly skewed. Although both of the trading volume series do not reveal remarkable departure from normality in the context of skewness, they are clearly non-normally distributed.

6.5. Correlations between Volatility and Trading Volume Series

6.5.1. Correlation Structure on the Same Trading Day

Correlation coefficients between volatility and volume series have been calculated in order to know correlation structures. The cross-correlation coefficients[28] and probability values of significance of correlation coefficients are presented in Table 3. below. All combinations of volatility and volume series are statistically significant and positively correlated with all common significance levels. Results are in accordance with most of the US studies reporting positive stock-price-trading-volume relationship.

Table 3. • Correlation Matrix. Probability values of the Pearson correlation coefficient test are presented in parenthesis. *, **, and *** denote rejection of the null hypothesis at 5%, 1%, and 0.1% significance levels, respectively.

Variables	*VOLAA*	*VOLAADS*	*TRADEA*	*TRADEADS*
VOLAA	1.000000 (0.0000) ***			
VOLAADS	0.513384 (0.0000) ***	1.000000 (0.0000) ***		
TRADEA	0.592642 (0.0000) ***	0.414204 (0.0000) ***	1.000000 (0.0000) ***	
TRADEADS	0.467413 (0.0000) ***	0.549224 (0.0000) ***	0.537090 (0.0000) ***	1.000000 (0.0000) ***

Correlations between the stock markets in the context of volatilities are lower than might be pre-expected. Correlation coefficients vary from the lowest value of 0.414204 (correlation between TRADEA and VOLAADS) to the highest correlation value 0.592642 (correlation between VOLAA and TRADEA). Volatility series have smaller correlation than trading volumes (0.513384 and 0.537090, respectively), although differences in the absolute values of the correlation coefficients are not very considerable.

The correlation coefficients between TRADEA and VOLAADS and between TRADEADS and VOLAA do not depart far from other correlation structures. The significance of the correlation coefficients of all combinations may be partly caused by the large number of the observations, but there are undoubtedly a clear positive correlation between these series.

[28] Test statistics are based on the Pearson's correlation coefficient. The null hypothesis is that the series are not correlated.

6.5.2. Lagged Correlation Structure

To be more convinced of correlation between the series, the effect of time difference has been checked. The correlation structure has been re-examined as above, but the series from the NYSE are lagged by one time period (one trading day). This procedure can be argued by means of different time zones between stock exchanges.

Table 4. Correlation matrix. Probability values of the Pearson coefficient test are presented in parenthesis. *, **, and *** denote rejection of the null hypothesis at 5%, 1%, and 0.1% significance levels, respectively. VOLAADS_1 and TRADEADS_1 denote a one day lag from VOLAADS and TRADEAS series.

Variables	*VOLAA*	*VOLAADS_1*	*TRADEA*	*TRADEADS_1*
VOLAA	1.000000 (0.0000) ***			
VOLAADS_1	0.369622 (0.0000) ***	1.000000 (0.0000) ***		
TRADEA	0.52642 (0.0000) ***	0.468627 (0.0000) ***	1.000000 (0.0000) ***	
TRADEADS_1	0.318506 (0.0000) ***	0.549221 (0.0000) ***	0.545575 (0.0000) ***	1.000000 (0.0000) ***

The correlation between series is consistently lower than in the case of same trading day. These findings encourage *in this phase of the study* the statement that the influence of Nokia ADS on Nokia A is minor than has been pre-expected. Table 4. presents the correlation structure between series of the HeSE at day *t* and the NYSE at day *t-1*.

The correlation between the lagged volatility of Nokia ADS and the volatility of Nokia A is 0.318506 which is smaller than in the case of the volatilities for the same day. This suggests that the dependence is greater on the same trading day than between the US one day lagged and today on the HeSE. The smallest correlation has been found between the lagged trading volume of Nokia ADS and the volatility of Nokia A. The greatest correlation coefficient has been between trading volume and volatility of Nokia A. This is consistent with the previous findings of the correlation matrix. Parallel to findings of the first correlation matrix, all combinations of the time series are statistically significantly positively correlated [29].

The lagged effect does not seem to make a clear difference on the correlation of TRADADS and TRADEA: the correlation coefficients have changed only marginally. Instead, the lagged volatility of Nokia ADS has increased the correlation coefficient with the trading volume of Nokia A. Based on the comparisons between lagged values of Nokia ADS, it can be said that the correlations between the series have decreased, but just on very small scale.

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[29] Nevertheless, it is worth to note that in the first correlation matrix the number of the observation was 537, whereas in the second matrix, due to the lagged variable, the number of observations was 536.

In conclusion, the behaviour of time series does have some dependency on the basis of the correlation coefficient. The correlation coefficients are approximately 0.5, on the same trading day, so it can be justified to conclude that the series are positively correlated. The correlations are smaller when the series of Nokia ADS have been lagged by one trading day. Although these correlation coefficients do not directly address the question of causality relationships between variables, they have indeed indicated the *possibility of causality* relationships between the trading volume and the intraday volatility series of Nokia A and ADS.

Replacement of outliers may reduce the skewness of the return distribution and move the kurtosis closer to what could be expected for a normal distribution. Furthermore, extreme values may seriously damage the values of correlation coefficients and other descriptive statistics. But removing extreme observation may lead to the loss of valuable information. In this context, the proper and deeper evaluation of extreme values is needed. The following section concentrates on listing extreme values of the series and giving possible explanations for these abnormal observations.

6.6. The Role of Outliers

6.6.1. The Detection of Outliers

The results in the literature have emphasised the importance of outlier analysis especially in financial data sets. This means more work, but e.g. in forecasting even a small decrease in the risk of false signals is worth the trouble. Data manipulation, that is omitting abnormal observations, can not be justified: removing abnormal observation from the data leads undoubtedly to the loss of valuable information concerning the time series.

In order to be confident about the existence of outliers in the data, Box-plots of each series have been applied[30]. The Box-plots of trading volumes and volatility series are presented in Figures 1. and 2. in the appendix. The great number of the outliers suggest that it is unreasonable to omit these observations from the data. As it can be seen from Figures 1. and 2. in the appendix, there are indeed several aberrant observations. The volatility series "suffer" from more extreme values than the trading volume series. This has been observed also by diagnostic statistics of the time series. However, there are many such observations which can be treated as outliers. But we would lose valuable information about the trading day if the aberrant observations were omitted from the time series. Additionally, if the aberrant observations are deleted, the time series no longer describe the real trading. Erasing observations bias the trading volume and volatility behaviour in the market which further bias the results of the forthcoming analysis: omitting observations will misrepresent the reality of the stock markets.

The reasons behind these abnormal observations are worth to considering and trying to find some explanation for these abnormal events. It is interesting to search for proper

[30] Normal time plots will not reveal the possible *masking effect*, in which the outlier covers one or several other outliers in a series. Chatterjee and Jacques (1994) have pointed out that typical cases of the masking effect can be found in share prices or similar financial time series.

explanations for the extreme values: surprising news about companies, their competitors, economies etc. may have caused the extreme values. The extreme values may have been also caused by market's overreaction, changes in "fashion", or related non-fundamental factors. Naturally, the fundamental factors may also have worked to create extreme values.

6.6.2. The Explanations of Observed Outliers

Hella (1996) has suggested that if some aberrant observations can be found, it is important to try to find proper interpretation for as many outlier as possible. In this context, it is worth mapping the news releases of the abnormal trading day. Five of the highest aberrant observations and the candidate explanations based on the press releases of Nokia Corporation on each time series are listed in Table 1. in the appendix[31].

The extreme lowest observations are not presented because the interest is keen on the highest values of volatility and trading volume changes. Something can be said about the low volatility and trading volume periods. Unusual low values have been reported for both stock series. Especially in the summer and August of 1994, there has been unusually low trading volume and volatility periods in both stock exchanges. At the end of 1994 and in the beginning of 1995 three unusually low volatility days took place on the New York Stock Exchange. An interesting era has also been in the second and third quarters in 1995, since the volume and volatility series were very stable: none extreme values during that period can not be reported.

Exceptionally low single values of trading volume or volatility have been observed on single days and thus no "depression" periods have been found. The very low trading volume and volatility days have been, however, found on the 3rd of August in 1994 in the NYSE and the 20th of September in 1994 in the HeSE. These exceptionally low activity days may be due to waiting for forthcoming more important information, temporarily short trading time in the stock exchange caused by holidays, computer or network failures or other similar factors suspending trading in the stock markets. However, this is pure speculation rather than arguing the real reasons for very low activity in the stock exchanges and there is no incentive to continue argue what may have been happened in the stock markets with low trading activity levels.

Almost half of the extreme values are in line with another abnormal observation. Approximately a third of the number of the extreme values are connected between the trading volume and volatility series. This suggests also that when volatility (volume) is abnormally brisk, the volume (volatility) has faced considerable changes[32]. Just one trading day is somewhat confusing: a very low trading volume of Nokia A and a very high trading volume of Nokia ADS happened on 31.3.1995. A day before 31.3.1995 there was Nokia's annual general meeting and dividend decision of FIM 10. Additionally, Nokia released the

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[31] The explanations of aberrant observations have been based on the Internet news services. Home pages, such as http://www.ft.com; htpp://www.hex.fi; http://www.kauppalehti.fi; http://www.nokia.com;http: //www.nyse.com; and http://www.wsj.com have been used to obtain the daily news and other releases for an explanation of new information and extreme values of the volatility and volume observations.

[32] Just based on extreme values, this is in accordance with the notice of Clark (1973). Further, it has been revealed with the concept of extreme low observations, that exceptionally (five smallest) low volume is often accompanied by with very low intraday volatility.

news of a DEM 800 contract on 30.3.1995. A very high trading volume in Nokia ADS shares in the NYSE confirm the importance of the new information released on 30.3.1995. However, no proper explanation for the unusually low trading volume can be found at Helsinki.

A unarguable trading day was 14.11.1995. Nokia A faced a very high volatility and Nokia ADS a very high trading volume period. The earliest news release was two days before 14.11.1995, so that might not be an explanation. However, Nokia did not release any news during that day. It is possible that the telecommunication industry, and especially rivals of Nokia, have announced some important information concerning the future of the telecommunication company or the whole industry. Sometimes when the trading volume has remained tiny, markets have argued that by the absence of news.

Extreme high volatility periods associated with very high trading volume have happened twice during the observation period. On the 17th and 18th of January 1996 Nokia Corporation has faced very high trading volume and volatility in both stock exchanges. "Turbulence" dominated two trading days. The reason for turbulence might be due to four news releases within three days. On January 16th and 18th Nokia announced a network contract to China´s emerging telecommunication markets. On the 17th of January Nokia adjusted its television set production and established a new production unit for automotive needs.

On April 1st 1996, Nokia announced its withdrawal from the television business. This news announcement might have been released near closing, because the next day Nokia A experienced a "windy" day: both volatility and trading volume have been exceptionally high compared to the values of the observation period as a whole. Additional impact certainly has come from Mr Iiro Viinanen´s joining the board of directors and the dividend decision of 3 FIM on 2nd of April in 1996.

In conclusion, half (6 days /12 "high") of the trading days of very high volatility and volume observation can be mapped onto the same trading day. This is clear evidence for the statement about high volatility association with high volume period. Moreover, it is worth noting that the high volatility and trading volume periods have followed after news releases, not on the contrary. This is in accordance with the well-known fact that investors react and update their expectations after the information arrives to the markets.

6.7. Differences within Volatility and Trading Volume Series

Even though the graphical presentations in Figures 1.- 4. have seemed to be quite similar between the volatility and trading volume series, it is however essential to deepen the knowledge of the differences of the two volatility series and two volume series. It has been investigated whether the difference of the volatility and volumes series of Nokia A and Nokia ADS have zero means. Differences of the series have been calculated as follows:

$$DIFFEVOLAA = VOLAA\text{-}VOLAADS \tag{5}$$

$$DIFFETRADE = TRADEA\text{-}TRADEADS \tag{6}$$

Table 5. Descriptive statistics. DIFFEVOLAA

Descriptive statistics	*DIFFEVOLAA*
Mean	-0.000605
Median	-0.000287
Maximum	0.136850
Minimum	-0.058712
Standard Deviation	0.017601
Skewness	1.496364
Kurtosis	14.39830
Jargue-Bera(Prob.)	3107.388 (0.00000)
Observation period	20.7.1994-9.8.1996
Sample size	537

Table 6. Descriptive statistics. DIFFETRADE

Descriptive statistics	*DIFFETRADE*
Mean	-0.408607
Median	-0.369243
Maximum	1.973190
Minimum	-4.787932
Standard Deviation	0.759939
Skewness	-0.764028
Kurtosis	6.557302
Jargue-Bera(Prob.)	335.3868 (0.00000)
Observation period	20.7.1994-9.8.1996
Sample size	537

Table 7. T-test. Difference between volatilities.

T-test	*DIFFEVOLA*
Null Hypothesis	*mean=0*
Alfa	0.05
T-statistic	-0.797111
Significance Level	0.4257

Table 8. T-test. Difference between volumes.

T-test	*DIFFETRADE*
Null Hypothesis	*mean=0*
Alfa	0.05
T-statistic	-12.4599
Significance Level	2.16049E-13 ***

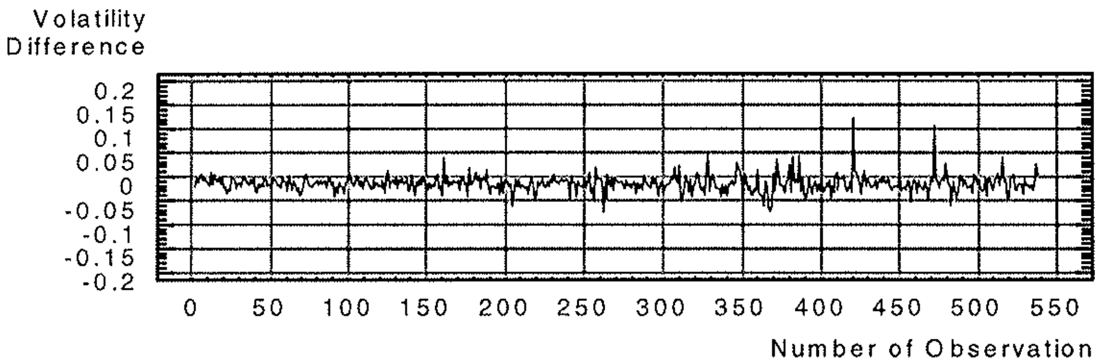

Figure 5. Time sequence plot. Volatility difference between Nokia A and ADS.

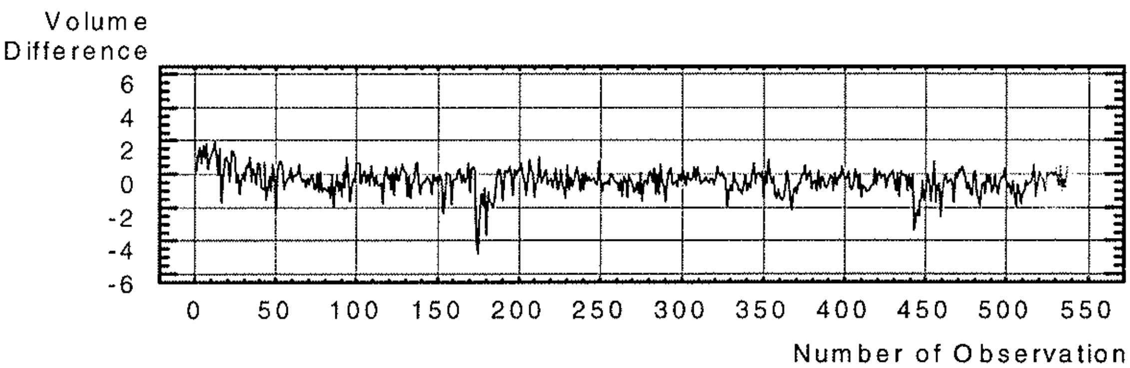

Figure 6. Time sequence plot. Volume difference between Nokia A and ADS.

If the null hypotheses of zero means are rejected, it can be inferenced that some statistically significant and permanent differences exist *on average* within the series. Descriptive statistics of DIFFEVOLAA and DIFFETRADE are presented in Tables 5. and 6. Figures 5. and 6. show the time sequence plots of the series. The results of the t-test are presented in Tables 7. and 8. below.

According to the t-tests, it is evident that the mean of DIFFEVOLA is zero, so *on average* there are not any statistically significant differences between the volatility series. Hence, accepting the null hypothesis suggests that the volatility behaviour is similar in the two stock exchanges. But in the case of trading volume, there indeed exists a statistically significant difference between trading volume series of Nokia A and Nokia ADS. In this context, it can be pointed out that relative changes are different (i.e. different from zero), it is even evident that absolute changes are remarkably different within the HeSE and the NYSE.

Looking to figures 5. and 6. above, the conclusion can be drawn that the volatility in Nokia ADS has been greater and only a few times Nokia A has experienced greater intraday volatility. However, the null hypothesis has been accepted, which indicates that there is no statistical difference between the volatilities. Parallel to the volatility series, the trading volume of Nokia ADS has exhibited dominance with respect to the corresponding series of Nokia A. But in the beginning of the observation period, the changes in trading volume of Nokia A has been greater.

Descriptive statistics suggest deeper investigation of volume-volatility space. In the following chapter the basic linear regression models have been estimated in order to find out if there is a positive, negative or insignificant relationship between these series.

7. THE LINEAR DEPENDENCES OF VOLATILITY AND VOLUME SERIES

7.1. Estimation Method

This chapter concentrates on the investigation whether volatility can explain changes in trading volume separately for each stock series. It is best to first test for heteroscedasticity rather than merely to assume that it is present. Hence, the models have been estimated by normal ordinary least squares method and then the presence of heteroscedastic disturbances have been tested with White´s heteroscedasticity test (1980). It has been found that the disturbances are heteroscedastic. Due to the heteroscedasticity of disturbance terms, estimation is henceforth based on the heteroscedasticity consistent estimators of the variance matrix of the regression coefficients.[33]

7.2. Regression Model of Nokia A

The focus is first on Nokia A. In order to find out if VOLAA can explain the changes of TRADEA the models can be described as follows:

$$TRADEA_t = \alpha + \beta_1 VOLAA_t + \varepsilon_t \qquad (7)$$

The results are presented in Table 2. in the appendix. In Nokia A case, it is clear that there is a positive relationship between volatility and volume space. Both estimates of regressors are statistically significant in equation (7). According to results from the estimated model, a one per cent increase in VOLAA leads to a 20.79 per cent increase in the TRADEA variable. Changes in volatility can explain approximately 35 per cent of changes in trading volume. The model is statistically significant (the probability of F-statistics is 0.00000). However, the disturbance terms of the model (7) exhibit clear departure from normality and non-autocorrelation structure. If the significance level is 1 % or greater, the disturbance structure does not have ARCH(1)-effect.

7.3. Regression Model of Nokia ADS

The same procedure as in Nokia A´s case has been applied to the American Depositary Share. On the Nokia ADS basis, the following model has been estimated. The results are presented in Table 3. in the appendix.

$$TRADEADS_t = \alpha + \beta_1 VOLAADS_t + \varepsilon_t \qquad (8)$$

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[33] White`s heteroscedasticity test is based on the OLS squared residuals regressed on dependent variable and its squared value from OLS regression (White 1980, and Peseran and Peseran 1991). The results from OLS estimation are not presented in the appendix in order to save time and space.

There is a positive association of the changes in the volatility and trading volume series of Nokia ADS. All estimated parameters are statistically significant: the probability value of the significant test for the model is zero (probability value of the F-statistic). The rate of determination indicates that the model can explain 30 per cent of the variation of TRADEADS. The absolute values of the estimated parameters are fairly similar within models (7) and (8). The differences are merely marginal so in this context the linear relationship are very similar between the stock exchanges. However, something about the differences of the estimates can be concluded: VOLAADS seems to have grater impact to changes of TRADEADS than VOLAA to TRADEA. Parallel to the results of Nokia A, there is undoubtedly evidence of the non-normal disturbances and ARCH(1)-effect. Additionally, the disturbance terms of Nokia ADS model exhibit greater autocorrelation than Nokia A.

In conclusion, there does not exist considerable differences among these estimated models. Both models explain approximately a third of the variation of the dependent variables. Considering the clear positive associations of the time series, it is essential to check whether causality and non-linear dependencies can be found between the volatility series of Nokia A and Nokia ADS. The same arguments must also be applied to the volume series.

Before applying causality and dynamic models, it is essential to explore certain properties, such as stationary and cointegration of the volatility and volume time series. If they are not stationarity some transformations are needed in the forthcoming analysis. Additionally, stationarity analysis will assist in the determination of the presence of trend and /or drift parameters of the series. These aspects are discussed, criticised and estimated in the following chapter.

8. INTEGRATION AND STATIONARITY OF TIME SERIES

8.1. Integrated Processes

Stationarity is a simplifying property in the analysis of time series. In practice, for the most macroeconomic variables stationarity is an empirical matter. There are some theoretical models postulating non-stationarity behaviour in time series, such as exchange rates and stock prices. In terms of economics, unit roots are associated with a concept of "persistency" of innovations or "shocks" to the economic system (Noriega-Muro, 1993, p. 1-5). In this context, it is important to explore the stationarity properties of the volatility and volume series. Before estimation, it is essential to point out some basic definitions, properties and traps in the empirical investigation of unit roots.

The degree of integration, *d*, of a time serie is important aspect in determing the statistical properties of time series. A serie is said to be integrated of degree one, I(1), if it becomes stationary after first differencing. It is fundamental to understood the properties and the differences between I(1) and I(0)-processes[34]. According to Mills (1993) and Enders (1995) among many others, the following properties in identification of *stationary* time series are helpful. A stationary process

1. Exhibits mean reversion in that it fluctuates around a constant long-run mean.
2. Has a finite variance that is time-invariant.
3. Has a theoretical correlogram that diminishes as lag length increases.
4. Innovation ε_t has just temporary effect on serie y_t.

A non-stationary time series has necessarily permanent components. The mean or/and variance of the nonstationary series are time-dependent. To aid in identification, it has been suggested e.g. by Enders (1995) for the *nonstationary* time series that

1. There is no long-run mean to which the series returns.
2. The variance is time-dependent and goes to infinity as time approaches infinity.
3. Theoretical autocorrelations do not decay but, in finite samples, the sample correlation dies out slowly.
4. Innovation ε_t has permanent effect on serie y_t because y_t is the sum of all the previous innovations.

More precisely, the importance of unit root test in financial data comes from the difference in responses of the variables to unanticipated shocks or innovations. To illustrate the role of the unanticipated shocks to the serie, the simple AR(1) model can be described as follows:

[34] The most macroeconomic time series can be described as an I(1)-processes. An I(2)-process is continuously growing serie. Some financial time series follow these processes, but an I(3) or a higher processes are very rare. Economic history have typically pointed out some examples of I(3)-processes, such as hyperinflation periods in Germany between the World Wars and in Hungary after the Second World War. (Greene, 1990)

$$y_t = \alpha y_{t-1} + \varepsilon_t \text{, where} \tag{9}$$

$$\varepsilon_t = i.i.d.(o, \delta_\varepsilon^2) \text{, t=1,..., T}$$

Model (9) can be solved to yield

$$y_t = \alpha^t y_0 + \sum_{i=1}^{t-1} \alpha^i \varepsilon_{t-1} \tag{10}$$

Following Dickey, et al. (1986), at least the first two of the following three cases, are of interest in economic time serie analysis. Firstly, if *0<α<1* then the process is *stable* and the shocks in the distant past go to zero as the sample size *T* increases. In this case the present is more important than the past. Secondly, in the case of *unit root,* *α=1* and then the influence of both y_0 and the accumulation of the previous shocks are equally important as the current shocks. This implies that the past and the present are equally important. For the latest, if *α>1*, the case is *explosive* one and indicates that the previous shocks becoming bigger as *T* increases.

To explore the properties of unanticipated shocks of series and hence stationarity, time serie analysis offer several methods. The most commonly used procedure, the Dickey-Fuller tests, and the properties of these tests are shortly reviewed in the following section.

8.2. Methods of Exploring Unit Roots

8.2.1. Overdifferencing and Outliers in Autocorrelation Plots

The importance of testing unit roots is based on the point that economic models may have equilibrium(s). Testing for unit root of time series, which is known also as cointegration analysis, is based on the idea that the given economic time series may not change freely or independently of each other.

Usually normal plot in sequence of time will tell the non-stationarity of time series. But the exact determination of the stationarity may be difficult by means of normal time dependent plot. Autocorrelationfunction (hereafter referred to as ACF) give a roughly indication of the existence of trend in time serie. Furthermore, Mills (1993) has emphasised that relaying just plot of ACF may cause overdifferencing problem[35]. It is important to note "indirect" correlations which are present in the ACF of any autoregressive process. Partial autocorrelation (PACF) eliminates the effects of the intervening values and correlations through different lag structures [36].

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[35] Overdifferencing may cause serious troubles. Extradifferences of stationary series produces stationary results. The variance of the overdifferenced process may be greater than the original process. The behaviour of the sample variance with different values of *d* will give valuable information for the right decision of *d*: the sample variance decreases until the stationary level is reached. The sample variance may will increase if too many differences has been taken. Comparing different sample variances is a trusty method for the right decision of difference level. (Mills, 1993, p. 52)

[36] In an AR(1)-case, the partial correlation between y_t and y_{t-2} is equal zero.

Most of the standard statistical methods are not able to protect against outliers[37]. It is a well-known that only one outlying (aberrant) observation can ruin the sample auto-correlation (cross-correlation) function estimates and the least square estimates (Hella, 1996, p. 1). Although the properties of a sample correlogram are useful tools for detecting the possible presence of unit roots, the method is necessarily imprecise, since slowly decaying ACF-plot may indicate unit root process or nearly unit root process. (Enders, 1995)

In this sense it is not recommended to drive just ACF- and APCF-plots and their test[38] in determination of stationarity of the series. More deeper methodology is needed, indeed. The most common methodology to determine stationarity are the Dickey-Fuller tests which are based the autoregressive presentations of time series.

8.2.2. The Dickey-Fuller and the Augmented Dickey-Fuller Tests

It is difficult task to determine the exact generation of time series process: should a time serie be detrended or differenced to reach stationarity. Unit root tests are common methodology for determine the right difference level. The Dickey-Fuller and Augmented Dickey-Fuller tests[39] are the most common unit root testing procedures. Dickey and Fuller (1979) have presented three formulas which can be applied in the investigation of stationarity. Three models are following:

$$\Delta y_t = \gamma y_{t-1} + \varepsilon_t \tag{11}$$

$$\Delta y_t = a_0 + \gamma y_{t-1} + \varepsilon_t \tag{12}$$

$$\Delta y_t = a_0 + a_1 t + \gamma y_{t-1} + \varepsilon_t \tag{13}$$

Differences between the three regressions concern the presence of the deterministic elements, a_0 and $a_1 t$. The first formula (11) is a *pure random walk model*, the second equation (12) adds *an intercept or a drift term*, and the third (13) includes both deterministic parameters, *a drift and a linear time trend.* The parameter of the interest is γ; if $\gamma=0$, then the serie y_t contains a unit root.

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[37] There is different definitions of an outlying observation. Typically an outlier is defined as an observation (or a subset of observations) which appears to be inconsistent with the remainder of set of data. (Hella, 1996 p. 1)

[38] The Box-Pierce Q-test can be used to test whether a group autocorrelations are significantly different from zero so serie is white noise process. A "small" improvement compared to the Box-Pierce test is the Box-Ljung test due to its superior performances in small samples (e.g. Enders, 1995, p. 87 and Green, 1993, p. 558).

[39] There exist several other unit root tests. Just few to name, the Bhargavan (1986) test has been found out to be the most invariant test when a process has described without lag parameters. Phillips and Oualiaris (1988) have utilised the long-run variance of serie Δx_t . Hall's (1989) instrumental method has been considered useful when serie x_t includes moving average component(s). More recently, testing for unit roots has approached of bayesian point of view (e.g. DeLong and Whiteman, 1991a and 1991b; Sims and Uhling, 1991; and Koop, 1992). However, the bayesian approach may take some time before more often applied within researchers. So far, the classical approach offers the most convenient and applied way in the analysis of unit roots.

The test involves estimating one (or more) of the equations above using OLS in order to obtain the estimated value of γ and the associated standard error. Comparing the estimated t-statistics with the appropriate critical values simulated by Dickey-Fuller[40] will assist for accepting or rejecting the null hypothesis $\gamma=0$. In the case of rejection the null the, the alternative hypothesis, i.e. no unit root (stationary time serie), is accepted at the chosen significance level.

The Dickey-Fuller -test can be applied when process is an AR(1). However, many series are not well enough described as a pure AR(1). For higher orders of autoregressive processes, the Augmented Dickey-Fuller test (ADF) can be applied. The ADF-test procedure assumes that the disturbance terms are identically and independently distributed random variables. Moreover, the number of the lags used in the ADF-test depends strongly on the sample size and the autocorrelation of the disturbance terms. Formulas (11), (12) and (13) can be replaced by the next autoregressive processes:

$$\Delta y_t = \gamma y_{t-1} + \sum_{i=2}^{p} \beta_i \Delta y_{t-i+1} + \varepsilon_t \tag{14}$$

$$\Delta y_t = a_0 + \gamma y_{t-1} + \sum_{i=2}^{p} \beta_i \Delta y_{t-i+1} + \varepsilon_t \tag{15}$$

$$\Delta y_t = a_0 + \gamma y_{t-1} + a_2 t + \sum_{i=2}^{p} \beta_i \Delta y_{t-i+1} + \varepsilon_t \tag{16}$$

The null hypotheses are similar as in the Dickey-Fuller test mentioned above. If $\gamma=0$, then a serie has a unit root. (Enders, 1995) The Dickey-Fuller unit root tests are relatively simple for modifications and inferences. However, some relevant problems and traps concerning the modifications and the robustness of the tests have to be emphasised.

8.3. The Model Specifications and the Robustness of the Dickey-Fuller Tests

Testing for unit roots has became a common practice in modelling univariate and multivariate economic time series from which the most are known to show a nonstationary patterns. There are some important aspects which have to be very carefully considered: in the very short-run and especially in forecasting purpose, the significance of trend parameter nonessential. Hence, the longer forecasting horizon will be, the more important is the relevance of right specification of trend and drift parameter in estimated models. (Enders, 1995)

[40] In their simulations Dickey and Fuller (1979) have found out that the critical values depends on whether a constant or/and a time trend have been included into models. Moreover, the critical values depend also on a sample size and a specification form of the model. Consistent to many other hypothetical testing procedures, the critical values of the t-statistic decreases when the sample size increases. Fortunately, almost all statistical and econometric softwares include the Dickey-Fuller critical values for all common significance levels. Econometric and statistical softwares give probability values which are good guide to correct inference: if the estimated probability value exceeds the chosen significance level (such as $\alpha=5$ %, 1% or 0.1%) the null hypothesis is accepted which suggest of the presence of unit root.

Making some *a priori* assumption about the existence trend and/or drift parameters is not well argumented, since the sample size used in the empirical analysis covers over two years. The data used in the estimation contains relatively recent 537 observations, so the sample size pictures well the recent development of the trading volume and intraday volatility behaviour of Nokia. On the one hand, sample have to considered quite short: two years covers just the recent development of the given series, so real long-run effects are unreachable. Usually the very long-run data cover of tens of years. But, on the other hand, in hectic and dynamic financial markets, two years may also be considered quite a long time horizon.

It would be wrong to make some a priori assumptions of the existence of, for example, trend parameter. We can not say that today's financial markets have became more volatile with respect to the past because considerable differences and structural changes have occurred in the markets. It is definitely essential to modify different specification of unit root tests in order to find some evidence against trend or/and constant parameters.

One problem which suggest to inference with care is the weak power of the Dickey-Fuller tests, especially if there is included too many or too few explanatory variables. The tests can not very well distinguish *almost* an unit root process and an unit root process of each other[41]. Secondly, the unit root tests are sensitive to the presence of deterministic regressors, such as a constants and a time trend variables. Several studies have pointed out that many economical time series have clear deterministic trends. However, the existence of clear deterministic trends has been questioned since time series may include also stochastic components. If the trend parameters is misspecified then also the hypotheses are also misspecified. Therefore, inappropriate variables in unit root tests may lead to wrong decisions. (Nelson and Plosser, 1982; Stock and Watson, 1988; and Enders, 1995)

The third aspects of the unit root test which complicates straightforward inference is the role of outliers. There exists evidence that e.g. additive outliers will establish a wrong identification: a time serie may be regarded as a stationary process when it is actually nonstationary. Taking into account the outliers of time series can lead to the non-rejection of unit root hypothesis (Lucas 1996, p. 89).

The fourth thing which must be considered carefully is the aspect of time and sample size. The null hypothesis (unit root) versus the alternative one (stationarity) depend only a very little on the number of observations itself. Instead data time span is very significant factor: the biggest power of the tests will be reached when the time span is the longest with the given number of observations. Contrary as a given time span, one extra observation in time serie has only just a marginal effect to the power of the tests. Thus, the longer is the time span and the less annual observation, the bigger power will be reached compared to the shorter time span such as the short daily series. (Shiller and Perron, 1985) Financial time series have typically very large number of observations, but a time span is not necessarily very long. In such a case, it is difficult to decide a right hypothesis: the null hypothesis (unit root) may be hard to reject even if it should be rejected based on statistics in terms of if the alternative hypothesis is close to a unit root: decisions may be wrong and misleading.

[41] For example, the correlogram of a stationary AR(1) process such that $\rho(1)=0.95$ will exhibit the type of gradual decay indicative of a nonstationary process.

The fifth problem in Dickey-Fuller tests is also in finding the true data-generating process of time series. For example, if a serie is generated with autoregressive and/or moving averages components, or has an ARMA-presentation, the degree of these components should be noticed in the unit root tests. The "wrong" choice of the degree of AR- and MA-processes lead undoubtedly to the biases of estimation of γ and its standard error[42]. Structural changes may have occurred in a economy and/or time series may have had seasonal variations. In these circumstances series must be seasonal adjusted and/or parameters of structural changes should be included into the models. Furthermore, time series may have more than one unit root. For example, Enders (1995) has presented a procedure for correction and eliminating these "disturbing" aspects.

The four step-by-step procedure developed by Doldado, Jenkinsin and Sosvilla-Rivero (1990) is a good guide in testing unit roots with different model specifications. Doldado et al. (1990) have recommended that testing for unit roots should be started with as simple model as possible. The role of the theory should be considered carefully in the unit root analysis, since included/excluded trend and/or drift parameters may depend on the theory behind of the research. In their research, Doldado et al. (1990) have stated that it is wise to concentrate on the AR-components and transformations (logarithms) of series and specify the models excluding drift or trend parameters if firstly estimated model included too many variables.

However, the procedure of Doldado et al. (1990) will not be applied in its deepest form, because the theory behind of this research may suggest non-existence trend parameter in the case of for example efficient market hypothesis: I can not say that the intraday volatility and the trading volume series a priori include trending or drifting parameters. All together, it is useful and recommended way to use different model specification, such as included trend, drift, varying difference levels if the exact data-generated process is not known.

8.4. Results and Conclusions of Unit Root Tests

8.4.1. Stationarity of Intraday Volatility of Nokia A and Nokia ADS

Some statistics of the Augmented Dickey-Fuller tests, such as degree of determination of the estimated model (R^2), standard error of regression (S.E.REG.), sum of squared residuals of the model (S.S.RES.), F-test for the significance of the model and its probability value, have been presented in Tables 4.-7. in the appendix. These statistics have been used to determine the stationarity of the series. Other descriptive statistics, such as Akaike´s Information Criteria (AIC), Schwarz Bayesian Information Criteria (SIC) and Durbin-Watson Statistics, have not been introduced because they have not offered clear differences within different specifications.

It has been difficult to determine the exact specification of the estimated model of VOLAA since there have been some mixing aspects: on the one hand the ADF-results have suggested that VOLAA is an I(0) -process with an intercept term if the chosen significance level is 5 % or 10 %. But on the other hand, VOLAA can be described as an I(0)-process

[42] A more detailed description of ARMA-presentation in testing of unit roots can be found in Enders (1995).

with intercept and trend at 1 % significance level. Descriptive statistics in Table 6. in the appendix suggest that there are some improvements if VOLAA has modelled as an I(1) - process. For example, R^2 and F-value have increased considerably, but standard error of regression and sum of squared of residuals have changed little.

There is a trade-off between I(0)- and I(1)-processes, because after the second differencing standard error of regressions and sum of squared residuals have increased. This is an example of overdifferencing, although R^2, F-statistics and ADF -statistic (in absolute measures) have increased. In conclusion, it can be said that VOLAA is an I(0)-process with intercept and trend specification, hence in the ADF tests the null hypothesis of unit root (non-stationarity) has been rejected with 1 % significance level. Furthermore, the smallest sum of the square of residuals is found in this model specification.

In the case of intraday volatility series from the NYSE (VOLAADS), the task for inference stationarity has been more difficult than in the previous case. If the 10 % significance level is chosen as an inference criteria, VOLAADS is clearly an I(0)-process with intercept parameter and an I(0)-process with intercept and trend parameters. These findings suggest that VOLAADS is already stationary in levels.

It is worth noting that if the significance level is 5% or smaller, the serie has to be considered nonstationary in levels and hence having a unit root. It might be wise to also use an I(1)-process with no intercept or trend parameter as a description of VOLAADS because the null hypothesis of non-stationarity has to be accepted if the significance level is 1% or 5%. All three specifications of I(1)-processes model reject the null hypothesis of the existence of a unit root at all significance levels and hence indicate more confident results for an I(1)-process.

For choosing the "right" specification model, it has been decided that VOLAA is an I(0)-process with drift and trend parameter. The intercept term included into the model has led to greater standard error of regression and sum of squared residuals. Additionally, with the intercept and trend specification, the model has a greater degree of determination and F-test statistic.

8.4.2. Stationarity of Trading Volume of Nokia A and Nokia ADS

In the context of trading volumes, it has been easily noticed that TRADEA does not have a unit root. This can be argued by the fact that the serie is stationary already in levels so further differences do not have to be taken. Stationarity in levels indicates that TRADEA is predictable in the long-run. The decision between models of with intercept and intercept plus trend have to be carefully considered. Based on the higher degree of determination and smaller sum of squared of residuals and standard errors of regression, it can be concluded that TRADEA is a unit root process with intercept and trend parameters.

Parallel to the trading volume on the HeSE, it is clearly inferenced that TRADEADS is stationary in levels and hence is an I(0)-process. The choice of model specification of a stationary series in levels has led to the choice of model with intercept and trend parameters. However, it is also possible to consider TRADEADS as an I(0)-process with intercept parameter. The exact choice is difficult because on the other hand the model with intercept has smaller R^2 and greater sum of squared residuals and standard errors of regression. It is secure to conclude - relying on the S.E.REG. and S.S.RES. values - that TRADEADS is a stationary serie in levels with intercept plus trend parameters.

8.4.3. Conclusion of Stationarity and Consequences

In conclusion, the series VOLAA, VOLAADS, TRADEA and TRADEADS are stationary in levels and hence do not have unit roots. The inference of the stationary level of the trading volume series has been relatively easy. TRADEA and TRADEADS can be described as an I(0)-processes with intercept and trend parameters. In the case of VOLAADS exact decision can not be made depending on the chosen significance level. The VOLAADS serie looks like an I(0)-process with intercept or an I(0)-process with intercept and trend at a 10 % significance level.

If the series are integrated with the same orders and are non-stationary in levels, they might be *cointegrated.* Because all the time series are considered to be I(0)-processes, standard statistical tools are applicable. If the series were integrated in same order and are nonstationary in levels, Johansen cointegration methodology should be applied to the series, for example [43]. The Granger-causality models require stationary time series and thus in the case of nonstationary series, so called error-correction parameters for capturing long-run effects should be included into models. However, no error correction presentation is needed because all the series are already stationary in levels[44]. As it can been seen in Tables 4.-7. in the appendix, the role of the trend parameter has to be carefully evaluated. The Augmented-Dickey Fuller tests have indicated that there might be a trend parameter in all the series. Thus, the role of different trending variables in the series are investigated in the following chapter.

8.5. Existence of Trending Variable in the Series

According to the results of the unit root tests, there is a need to investigate the presence of a trending variable in the volatility and volume series, indeed. However, the problem is what kind of trend variable to incorporate into the series: is it possible to assume that just removing the mean or linear trend can obtain the best description of the trending variable[45]?

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43 For the reference of Johansen cointegration methodology, see *inter alia* Johansen (1988 and 1991) and Johansen and Juselius (1990) and for the evaluation of Johansen methodology, Gonzalo (1994), Cheung and Lai (1993), and Lee and Tse (1995). Detailed analysis of the concept of cointegration has been provided by Granger (1986), Engle and Granger (1987), Dickey and Rossana (1994) and Enders (1995).

44 More detailed descriptions of error-correction presentation, estimation and inference can be obtained for example in Greene 1990, Enders, 1995 and Mamingi, 1996.

45 As noted earlier, it is not possible to assume *a priori,* that changes of trading volumes are constantly upward trending even if investing has experienced a considerable increase. It is more than questionable to state *ad hoc* that volatility has increased during the observation period: a proper evaluation of the presence of different trend parameters are needed.

The procedure for the choice of the proper trend variable is the following. First, five different types of trending variables have been removed from VOLAA, VOLAADS, TRADEA and TRADEADS. The first type of trending variable is a mean. The rest of the trending variables are first, second, third and fourth order polynomials (linear, quadratic, etc. trend). The second step in evaluation of the best trending variables in series is their description capabilities of the original series. This is done by subtracting one of the candidate trending variables from the original series. The final step evaluates, by means of descriptive statistics, the description capabilities of the original series. The variable which has the best properties to describe the behaviour of the original series is chosen for the later analysis.[46]

Stated shortly, mean removing is the best trending variable for all the series. The differences between trending variables are very marginal, but removing the mean from the series describes the best the behaviour of the original series. Descriptive statistics of the subtractions of the original series and candidate trending variables are presented in Tables 8.-11. in the appendix.

Henceforth the original series are transformed so that the mean of each series has been removed. The names of the series are the same in order to avoid confusion between several variable names. From now, VOLAA and VOLAADS denote intraday volatility series of Nokia A and ADS. Correspondingly, TRADEA and TRADEADS denote log trading volume series of Nokia A and ADS, respectively. The following step in this empirical analysis is to map the Granger-causality relationship between these four transformed series. First, some basics of Granger-causality analysis is illustrated and criticised. Finally the series are put in the vector autoregression system (hereafter referred to as VAR-system) to find out the Granger-causality relationships. These things are done in the following chapter.

[46] Trended variables can be argued by means of common trend variable. It is possible - and probable - especially between volatilities of Nokia A and ADS and secondly trading volumes of Nokia A and ADS, that they have similar trending properties in the original series. Thus removing the "best" trending variable avoids the co-movements within series.

9. GRANGER-CAUSALITY MODELS

9.1. Motivation for the Study of Causalities

The long-run movements of volatilities and trading volumes are related to some extent. If short-run dynamics have been allowed for series, the causality analysis may offer valuable and useful information for predicting volatility and volume changes. But, given the non-experimental nature of the most economic data it is difficult - and often impossible - to determine causal relationships from time series. Therefore, economic theory usually has to provide a model that postulates the direction of causality relationships. Since many controversial economic theories exist, it would be preferable to examine such models including the causal directions with statistical tools. (Judge et al. 1985)

The comparison among these series may give valuable information about volatility *lead-lag associations* in two stock exchanges, the Helsinki Stock Exchange and the New York Stock Exchange. Correspondingly, the Granger-causality[47] analysis has also been applied to cover the trading volumes of Nokia A and ADS in order to know whether the volatility is the volume driving or vice versa [48]. If there are clear Granger-causality relationships between variables, information asymmetry is present. In addition to this asymmetry, revealed lead-lag associations are thought to be evidence of sequential arrival of information to the markets.

9.2. The Choice of Lag Lengths

9.2.1. Concerns about Lag Lengths

One of the most important aspect in the econometric analysis is how well the estimated model fits the data. Adding additional lags will necessarily reduce the sum of squares of the estimated residuals. However, adding such lags entail the estimation of additional coefficients and loss of degrees of freedom and inclusion of extraneous coefficients will reduce the forecasting performance of the fitted model. (Enders, 1995)

Gujarati (1995) has pointed out that the direction of causality may depend critically on the number of lag terms included, so the decision of number about lags is essential to make carefully[49]. It has been suggested by several studies to use more rather than fewer lags even if the loss in the degrees of freedom. Furthermore, Mamingi (1996) has emphasised that a

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[47] For an alternative causality test, known as Sim's test, see Christopher A. Sims (1972): "Money, Income, and Causality," American Economic Review, vol. 62, September 1972, pp. 540-552. Sims' test of causality includes not only the lagged and current terms of variables, *but also* future, or lead, values of the regressors. Regressor terms such as y_{t+1}, y_{t+2}, etc. are called lead terms. If y_t Granger-causes x_t, the sum of the coefficients of the lead y_t terms must be statistically equal to zero. However, the choice between Granger and Sims causality tests is not clear. For further discussion of these tests, see Chamberlain, G (1982): "The General Equivalence of Granger and Sims Causality", Econometrica, 50, 1982, pp. 569-582.

[48] The usual methods involve causality tests between volatility and trading volume, which is assumed to reflect speculation. However, these low power tests generally fail to reflect causal relation going from trading volume to speculation. (Stein, 1991, p. 28)

[49] One approach for lag lengths decisions can be based on the *ad hoc* basis and thereafter check the robustness of that choice.

large data span is more detrimental to true Granger-causality between variables than a large sample size. These main results of causality models have to carefully concluded, although the data used in the analysis is shorter in its span than its sample size. However, the Granger-causality tests all suffer from a major shortcoming, that is the arbitrariness in the choice of lags. To overcome such a shortcoming, Bahmani-Oskooee et al. (1991) have employed an approach of combing Granger-causality test with Akaike`s final prediction error (FPE) criterion.

There exist various model selection criteria that trade off a reduction in the sum of squares of the residuals for a more parsimonious model. Adding additional lags to the estimated model may cause worse forecast ability of the model than with fewer lags[50]. The two most commonly used model selection criteria are the Akaike`s information criterion (AIC) and Schwarz Bayesian criterion (SBC), calculated as

$$AIC=T*ln(RSS)+2n \tag{17}$$

$$SBC=T*ln(RSS)+n*ln(T), \tag{18}$$

where RSS = residual sum of squares

n = number of parameters estimated (p+q+constant term)

T = number of observations

Ideally, the AIC and SBC will be as small as possible. Model A is said to fit better than model B if the AIC (or SBC) for A is smaller than that for model B. (Enders, 1995) Two important issues, the choice of lags and the characteristics of the data, must be dealt with properly: causality tests are sensitive to non-stationary time series, incorrect lag lengths, model-selection criteria, and functional form. (Thornton and Batten, 1985; Roberts and Nord, 1985; Sims et al., 1986; Sephton, 1989; Kwan et al., 1995; and Xu, 1996)

9.2.2. Grounds for the Choice of Lags

Martikainen et al. (1994) have applied a different approach to decide the "right" number of lags. They have used three lags in their analysis of linear and non-linear dependencies between stock returns and trading volumes in the Finnish stock markets. Martikainen et al. (1994) have justified their three lags decision by means of the statistical significances of the estimated parameters: the longest lag which has been statistically different from zero (i.e. statistically significant) is the latest lag included into models. Their analysis has relieved that the third lag was the latest which was statistically different from zero. As Enders (1995, p.227) has suggested, this methodology is usual procedure to decide "right" lag structure.

There is some shortage of the research of Martikainen et al. (1994), hence they have not reported how robust the results have been within different time horizons. Furthermore, it is possible that after the first insignificant lag the next greater lag(s) will exhibit statistically

[50] Overfitting is called the case where randomly selected additional lags are included into a model. The overfitted model may outperform the original one, but it is likely to yield poorer forecasts. (Enders, 1995, p. 98)

significant properties. In this sense the lag length choice by Martikainen et al. (1994) is questionable and may not be further applied. This is the case especially in the Finnish stock markets which has faced considerable structural and institutional changes in the nineties.

The number of the lags has usually been restricted from one to five. This has been the accustomed way especially in research of financial markets since five trading days is a relatively long time period in hectic financial markets. The choice of lags used in this analysis could be based on either AIC or SBC. Both of the criteria have their own good properties: on the one hand the marginal cost of adding regressors is greater with the SBC than the AIC since *ln(T)* will be greater than 2 and then the SBC will always select a more parsimonious model than the AIC. But on the other hand, the SBC has superior large sample properties and is asymptotically consistent, whereas the AIC is biased. (Enders, 1995, p. 88) Typically, different information criteria give usually parallel solutions for the choice of the lag lengths[51].

A notable point is the fact that the appropriate choice of lag length does not mean optimal choice. These two information criteria rely solely on the properties of time series. Green (1993, p. 245) has emphasised that information criteria do not notice by any means the theory behind the analysis. As well, this work is based on empirical analysis, so it is *not* recommended to make the lag length decision on *ad hoc* basis.

Using different causality model specifications, such as varying lag lengths and time horizons, it is possible to conclude that instability of parameters exists and hence possible changes in causality relationships. If the number of lags have been kept constant and time horizons have been unchangeable, there is great danger of ignoring valuable information and changes of causalities between trading volumes and intraday volatilities. Based on the estimation results, the lag length has been restricted from one to five lags. Five lags includes information of volatility and trading volume process for five days ago.

9.3. The Granger Test

The Granger-causality modelling has received considerable attention in applied research. The Granger-causality test assumes that the information relevant to the prediction of the respective variables, x_t and y_t , has been contained solely in the time series data on these variables. The test involves estimating the following regressions as a VAR-presentation:

$$\Delta x_t = \delta + \sum_{i=1}^{a} \alpha_i \Delta x_{t-i} + \sum_{j=1}^{b} \beta_j \Delta y_{t-j} + v_{1t} \tag{19}$$

$$\Delta y_t = \rho + \sum_{i=1}^{m} \gamma_i \Delta y_{t-i} + \sum_{j=1}^{n} \lambda_j \Delta x_{t-j} + v_{2t} \tag{20}$$

where x_t and y_t are the time series of the interest, Δ is the difference operator, δ and ρ are constants, α_i, β_i, γ_i, and λ_i are parameters. Causality tests require stationary variables,

[51] In the estimation of causality models it has indeed have revealed that two information criteria give parallel results concerning the "right" level of lag length.

otherwise the F-statistic of the estimated models will have non-standard distribution, and the results will be misleading (Sims et al., 1986; and Xu 1996)[52]. Furthermore, it has been assumed that the disturbance terms v_{1t} and v_{2t} are uncorrelated. According to Gujarati (1995, p. 620), it is possible to distinguish four cases:

1. *Unidirectional causality from y_t to x_t* is indicated if the estimated coefficients on the lagged y_t in (19) are statistically different from zero as a group (i.e. $\Sigma \beta_j \neq 0$) and the set of estimated coefficients on the lagged x_t in (20) is not statistically different from zero (i.e. $\Sigma \gamma_j = 0$).

2. Conversely, *unidirectional causality from x_t to y_t* exists if the set of lagged y_t coefficients in (19) is not statistically different from zero (i.e. $\Sigma \beta_j = 0$) and the set of the lagged x_t coefficients in (20) is statistically different from zero (i.e. $\Sigma \lambda_j \neq 0$).

3. *Feedback, or bilateral causality*, is suggested when the sets of x_t and y_t coefficients are statistically significantly different from zero in both regressions.

4. Finally, *independence* is suggested when the sets of x_t and y_t coefficients are not statistically significant in both regressions.

Since the future cannot predict the past, if variable y_t Granger-causes variable x_t, changes in y_t should *precede* changes in x_t. Therefore, in a regression of x_t on other variables (including its own past values), if the past or lagged values of y_t have been included and it significantly improves the prediction of x_t, it can be say that y_t Granger-causes x_t. A similar definition applies if x_t (Granger) causes y_t. The null hypothesis is H_0: $\Sigma \gamma_i = 0$, that is, lagged y_t terms do not belong into the regression. The F-test statistic rejecting the null hypothesis is the following:

$$F = \frac{(RSS_R - RSS_{UR}) / m}{RSS_{UR} / (n-k)}, \text{ where} \tag{21}$$

RSS_R = residuals sum of squares from the restricted regression

$$\Delta x_t = \delta + \sum_{i=1}^{b} \beta_j \Delta y_{t-j} + \varepsilon_t$$

RSS_{UR} = residuals sum of squares from the unrestricted regression

$$\Delta x_t = \delta + \sum_{i=1}^{a} \alpha_i \Delta x_{t-i} + \sum_{j=1}^{b} \beta_j \Delta y_{t-j} + \varepsilon_{1t}$$

m = the number of the lagged y_t terms

k = the number of estimated parameters in the *unrestricted* regression

n = the number of observations

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[52] Charemza and Deadman (1992) have emphasized that causal models, such as VAR-model above, are strictly appropriate only when the variables are stationary. For nonstationary variables, however, they may be valid only approximately, or not at all (Charemza and Deadman, 1992). In this context, it has been essential to complete some stationarity tests, as has been done in chapter eight.

The F-test follows the F-distribution with m and $(n-k)$ degrees of freedom. If the estimated F-value exceeds the critical F-value at the chosen level of significance, the null hypothesis is rejected, in which case the lagged y_t terms belong in the regression. This is another way of saying that y_t causes x_t. (Gujarati, 1995)

9.4. Estimation, Results and Conclusions

9.4.1. The Presentation of Estimation Procedure

The empirical estimation of causalities has been divided into four parts[53]. The first part has concentrated on the volume-volatility relationships of each stock series Nokia A and ADS separately. The second part focuses first on the volatility behaviour at the two stock exchanges. The third part of the Granger-causality investigation is the volatility of Nokia A and the trading volume of Nokia ADS. The last part is Granger-causality testing whether the volatility of Nokia ADS Granger-causes the trading volume of Nokia A or vice versa.

The estimation has been carried out first by using the whole observation period and then by dividing the observation period into two subperiods in order to know the possible instability of parameters and hence changes in causality in the course of observation period. The results have described only by the models of F-statistics and their probability values and the inference for rejection of the null hypothesis.

The estimated models include the following parameters and series. Time series VOLAA, TRADEA, VOLAADS, TRADEADS denote intraday volatility and trading volume of Nokia A and intraday volatility and trading volume of Nokia ADS, respectively. The models are estimated with different model specifications, lag parameter k varies from 1 to 5.[54] *Sigma* and *rho* are constants, *alfa, beta, gamma* and *lambda* are parameters to be estimated and v-terms are disturbance terms which are assumed to follow normal (Gaussian) distribution. The following models have been separately estimated in order to find out Granger-causality relationships between volatility and volume series of both Nokia A and Nokia ADS.

[53] Due to the trending variable removals, I have also estimated the whole Granger-causality procedure below *with untrended data*. In order to save space and time, the results are not presented in the appendix. The results consistently show similar causality relationships, *but* in many cases with smaller significance, that is, with smaller F-test statistics and probability values. The results can be, however, obtained from the author by request.

[54] In such a model specification where time series from two different stock markets are used, it is essential to take into account the time difference between markets. As noted by Hedvall et al. (1997) the time difference between Helsinki and New York is 6,7, or 8 hours depending on whether the countries are in summer or winter time. In this context, some lag structures of the estimated models yield not only time lags but also the same trading day variables. These model specifications are different from those typically presented by Granger-causality models in text books and software. In this sense, care should be pointed towards correct lag structures in order to have correctly specified models.

9.4.2. Granger-Causality between Volatilities and Volumes

The first Granger-causality model explores the causality relationship between volatility and trading volume series separately for Nokia A and ADS. The estimated model can be described as follows:

$$VOLAA_t = \delta + \sum_{i=1}^{k} \alpha_i VOLAA_{t-i} + \sum_{j=1}^{k} \beta_j TRADEA_{t-j} + v_{1t} \tag{22}$$

$$TRADEA_t = \rho + \sum_{i=1}^{k} \gamma_i TRADEA_{t-i} + \sum_{j=1}^{k} \lambda_j VOLAA_{t-j} + v_{2t} \tag{23}$$

Null Hypothesis: VOLAA is not Granger caused by TRADEA
Alternative Hypothesis: VOLAA is Granger caused by TRADEA

$$VOLAADS_t = \delta + \sum_{i=1}^{k} \alpha_i VOLAADS_{t-i} + \sum_{j=1}^{k} \beta_j TRADEADS_{t-j} + v_{1t} \tag{24}$$

$$TRADEADS_t = \rho + \sum_{i=1}^{k} \gamma_i TRADEADS_{t-i} + \sum_{j=1}^{k} \lambda_j VOLAADS_{t-j} + v_{2t} \tag{25}$$

Null Hypothesis: VOLAADS is not Granger caused by TRADEADS
Alternative Hypothesis: VOLAADS is Granger caused by TRADEADS

The results in Tables 12.-14. in the appendix show that volatility is the driving force in Granger-causality relationship between volatility and trading volume of Nokia A. The null hypothesis, VOLAA does not Granger cause TRADEA, is rejected with all lag lengths in the total observation period. However, after splitting the whole observation period into two subsamples, the causality relationship is not so evident in the first subsample, but still indicates that VOLAA causes TRADEA. There is however some evidence of the inverse effect, that is causality from TRADEA to VOLAA, in the second subsample with one lag model specification. In this context, it is safe to conclude that *Granger-causality drives from VOLAA to TRADEA.*

In the case of Nokia ADS, only marginal evidence of Granger-Causality from VOLAADS to TRADEADS can be reported with 95 % significance level. The results are robust because the different time spans produce consistent results. The findings can be found in Tables 15.-17. in the appendix. It can be inferenced that *VOLAADS and TRADEADS are independent,* clear Granger-Causality relationships can not be found with any significance levels and time spans. These varying results between stock exchanges may be due to the size of the market: there are far many more stocks traded on the NYSE than on the HeSE. More liquid stock markets have to be considered more effective, unpredictable and non-existence of clear causalities.

9.4.3. Granger-Causality between VOLAA and VOLAADS

The next step is to analyse whether there exists Granger-causality relationship between volatilities of Nokia A and ADS. The model which has been estimated is the following

$$VOLAA_t = \delta + \sum_{i=1}^{k} \alpha_i VOLAA_{t-i} + \sum_{j=1}^{k} \beta_j VOLAADS_{t-j} + v_{1t} \tag{26}$$

$$VOLAADS_t = \rho + \sum_{i=1}^{k} \gamma_i VOLAADS_{t-i} + \sum_{j=0}^{k} \lambda_j VOLAA_{t-j} + v_{2t} \tag{27}$$

Null Hypothesis: VOLAA is not Granger caused by VOLAADS
Alternative Hypothesis: VOLAA is Granger caused by VOLAADS

Results of volatility causalities are reported in the appendix in Tables 18.-20., using different model specifications in order to know the instability of causalities. There is *very clear evidence of bi-directional causality between the volatility series*: very strong evidence in the total observation period of feedback effect can be stated with all five different lag structures. Thus, we can not say that the volatility showers come from the NYSE as stated by the press. But in the smaller observation periods the results are exciting. Feedback effect between volatility series is evident in the first subperiod, although not so strong as in the total observation period, although the one-way causality from VOLAA to VOLAADS is stronger than the feedback effect. But if we consider the different estimated models together, we can inference that VOLAA Granger-causes VOLAADS in the first subperiod. This statement can be argued by significance levels. Parallel to the first subsample, the results of the latter sample suggest also that intraday volatility of Nokia ADS is Granger-caused by the volatility behaviour of Nokia A. There is also weak evidence of feedback because the two lag models for testing the null hypotheses that VOLAADS does not Granger-cause VOLAA are rejected with a 1 % significance level. These results are in accordance with the findings of Liljeblom (1995) and Hedvall et al. (1997) where they have concluded that the markets affect each other in terms of price and returns processes. However, I can not state that there is an axiom of the causality relationships with different time spans and model specifications.

9.4.4. Granger-Causality between TRADEA and TRADEADS

The next step of the Granger-causality examination is to find out whether trading volume on the HeSE (TRADEA) and the NYSE (TRADEADS) have been somehow Granger-caused by each other. The models for linear dependencies of trading volume series of the two stock exchanges can be described as following

$$TRADEA_t = \delta + \sum_{i=1}^{k} \alpha_i TRADEA_{t-i} + \sum_{j=1}^{k} \beta_j TRADEADS_{t-j} + v_{1t} \tag{28}$$

$$TRADEADS_t = \rho + \sum_{i=1}^{k} \gamma_i TRADEADS_{t-i} + \sum_{j=0}^{k} \lambda_j TRADEA_{t-j} + v_{2t} \tag{29}$$

Null Hypothesis: TRADEA is not Granger caused by TRADEADS
Alternative Hypothesis: TRADEA is Granger caused by TRADEADS

Estimated F-statistics and probability values are reported in Tables 21.-23. in the appendix. *Independence between trading volume series in the total observation period is fairly evident,* although one may also suspect also support for the theory that TRADEA Granger-causes TRADEADS with one lag model specification. The Granger-causality from TRADEA to TRADEADS is more weakly measured with significance levels, but still indicates Granger-causality from TRADEA to TRADEADS. The importance of trading on the HeSE with respect to trading volume on the NYSE can be concluded in the latter subperiod: it is clear that trading volume behaviour in Helsinki Granger-causes trading activity in New York. In the context of these varying results, the Granger-causality relationships between trading volumes are somewhat obscure: the inference of *exact* Granger-causality relationships can not be made due to varying results depending on observation period and lag structures. However, there is certain evidence which stress the role of trading volume on the HeSE.

9.4.5. Granger-Causality between VOLAA and TRADEADS

The next step in the Granger-causality analysis is the causality relationship between VOLAA and TRADEADS. The following model has been estimated to conclude if VOLAA Granger-caused by TRADEA or vice versa.

$$VOLAA_t = \delta + \sum_{i=1}^{k} \alpha_i VOLAA_{t-i} + \sum_{j=1}^{k} \beta_j TRADEADS_{t-j} + v_{1t} \tag{30}$$

$$TRADEADS_t = \rho + \sum_{i=1}^{k} \gamma_i TRADEADS_{t-i} + \sum_{j=0}^{k} \lambda_j VOLAA_{t-j} + v_{2t} \tag{31}$$

Null Hypothesis: VOLAA is not Granger caused by TRADEADS
Alternative Hypothesis: VOLAA is Granger caused by TRADEADS

Estimated F-statistics and probability values are reported in Tables 24.-26. in the appendix. Support for the theory that VOLAA Granger-causes TRADEADS can be reported, although there is also some evidence of a feedback effect with one lag model specification. It is clear that TRADEADS is Granger-caused by VOLAA during the two subperiods separately. However, some decline can be found in the causality relationship in the first subperiod with respect to the latter subperiod, although the causality relationship remains statistically significant at the 1 % level in every lag structure modification. Based on these notes mentioned above it is fairly safe to infer *that volatility in Helsinki Granger causes trading volume in New York.*

9.4.6. Granger-Causality between VOLAADS and TRADEADS

The latest part in the Granger-causality investigation is concentrated between the trading volume of Nokia A and the volatility of Nokia ADS. The model to be estimated can be written as follows:

$$VOLAADS_t = \delta + \sum_{i=1}^{k} \alpha_i VOLAADS_{t-i} + \sum_{j=0}^{k} \beta_j TRADEA_{t-j} + \nu_{1t} \tag{32}$$

$$TRADEA_t = \rho + \sum_{i=1}^{k} \gamma_i TRADEA_{t-i} + \sum_{j=1}^{k} \lambda_j VOLAADS_{t-j} + \nu_{2t} \tag{33}$$

Null Hypothesis: VOLAADS is not Granger caused by TRADEA
Alternative Hypothesis: VOLAADS is Granger caused by TRADEA

Tables 27.-29. in the appendix show that *Nokia ADS's volatility is Granger-caused by the trading volume of Nokia A but the results are very unstable within different time spans.* In the first subsample there is quite clear independence between series, but in the latter subsample the same Granger-Causality relationship as in the total observation period can be found again. There is little evidence of bilateral causality or feedback in different observation periods: weak evidence of bilateral causality can be found only in the total observation period.

9.4.7. Conclusions of Granger-Causalities

It can be on an aggregate level (omitting different lag structures) concluded the following Granger-causality relationships of four mean-removed volatility and volume series. Graphical presentation has been drawn in Figures 7., 8. and 9. in order to picture as a whole the somewhat varying Granger-causality relationships. The dashed lines denote "suspects", that is the one revealed to be the least statistically significant of the Granger-causality relationships in the estimated models. The solid lines describe the conclusions of causality relationships. The lines without arrows denote independence between the time series.

My approach is to investigate Granger-causality relationships with different significance levels. Hence I have not had any a priori expectations of causality relationships of these series. On these grounds, I present all possible inferences, that is rejecting the nulls with varying significance levels. If I have chosen one significance level of the most common 0.1, 1, or 5 per cent, the inference would be misleading and hence misrepresent the causality relationships.

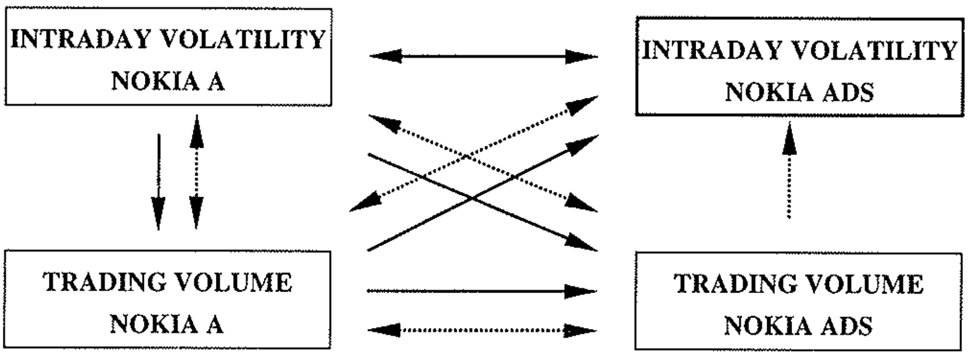

Figure 7. Graphical presentation of Granger-Causality relationships. **Observation period 1-537.**

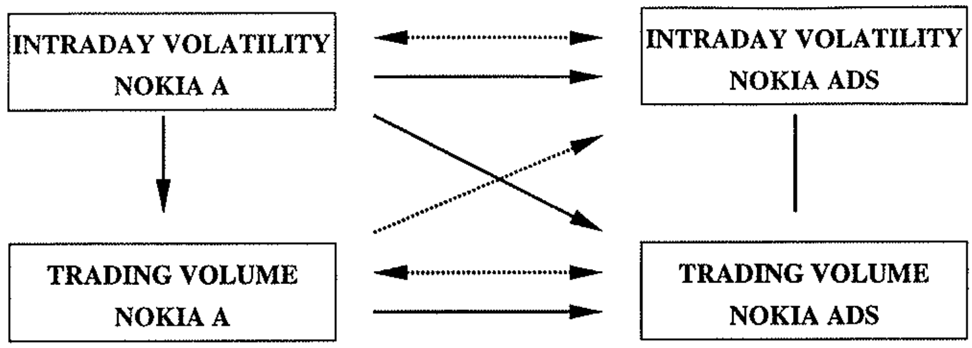

Figure 8. Graphical presentation of Granger-Causality relationships. **Observation period 1-268.**

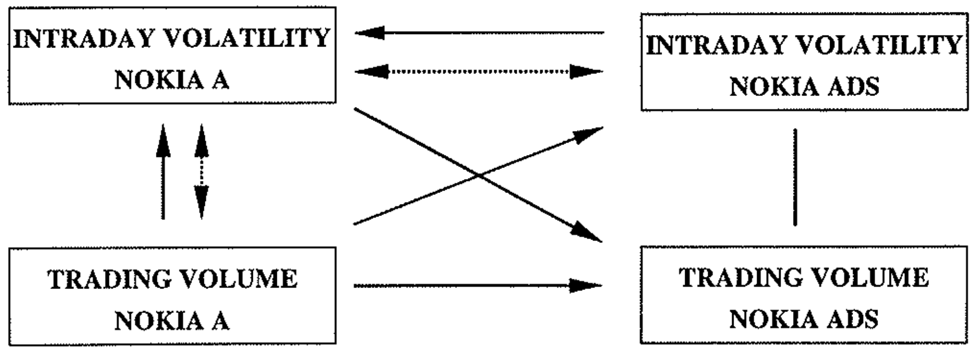

Figure 9. Graphical presentation of Granger-Causality relationships. **Observation period 269-537.**

At the first glance the three pictures may look like there exists no clear and consistent Granger-causality relationship between time series with different model and time span specifications. However, something can be said as an axiom about these series. There exists evidence that there is feedback or bi-directional Granger-causality between the volatility series. Independence between series of Nokia ADS in New York can be concluded. From a trading volumes point of view, it looks like the trading volume on the HeSE Granger-causes the correspondent in New York, although feedback effects in the total and first subsamples are probable. Interesting results come from the cross-sectional relationships of trading volumes and volatilities. On the one hand VOLAA Granger-causes TRADEADS, but on the other hand TRADEA seems to Granger-causes VOLAADS. However, the "confusion" is decreased with the note that there exists also some feedback effects in both cases during the whole observation period.

In summary, it is clear that there exists no exact coherence within all these series: the results have varied depending on the observation numbers and model specifications. This suggests that the intraday volatility and trading volume behaviours are complicated matters between markets. We can not state without contradictions that the role on the NYSE or the HeSE is more important. Non-existence of unquestionable Granger-causalities between stock markets suggest that there is simultaneous information delivery across markets. These aspects are in favour of the concept of informational efficient markets.

In spite of some feedback effects and varying results with different time spans and model specifications, deeper understanding of the volatility of Nokia A is needed, indeed. Thus, the deeper analysis has focused on mapping the *dynamic* relationship between volatilities. Recursive estimation is carried out in the following section in order to be more confident of the causality relationships between the dependent variable VOLAA and the explanatory variables VOLAADS and TRADEADS and the lagged VOLAA. The aim is to produce some models which determine Nokia A´s volatility behaviour. These modelling aspects of Nokia A´s volatility are done in the following section.

9.5. Recursive Estimation

9.5.1. Arguments for Recursive Estimation

Due to somewhat inconclusive and non-exact Granger-causality relationships between the time series, the question of how the estimated parameters have changed during the observation period has arisen. Modelling Nokia A´s volatility has been chosen for deeper analysis and for further checks of the behaviour of estimated parameters. The aim of the recursive estimation procedure is to produce the best dynamic model to describe volatility of Nokia A. Different model specifications are evaluated by means of significance levels of estimates and some tests for properties of disturbances: normality, serial correlation, heteroscedasticity and ARCH-effect of disturbances have been investigated. First, the model has been extended to cover the same lag structures in explanatory variables VOLAA and VOLAADS. After having a clear picture of how many lags should be included as a whole, the lag structures have been allowed to vary within explanatory variables. Finally, the trading volume series of Nokia ADS has been included due to the Granger-causal relationship in order to obtain some additional information in determing the intraday volatility behaviour of Nokia A.

9.5.2. Modelling Nokia´s Volatility by VOLAA and VOLAADS

The following model has been estimated in order to know how long lasting is the past information of volatility series for explaining Nokia A´s intraday volatility.

$$VOLAA = \alpha + \sum_{i=1}^{n} \beta_i VOLAA_{t-i} + \sum_{i=1}^{n} \gamma_i VOLAADS_{t-i} + \varepsilon_i \qquad (33)$$

The estimation procedure has been divided into three steps. First, one period lagged variables have been included and then two lags and finally three lags. It has been revealed that third lag is the first one which is statistically insignificant.

All model specifications from the one lag to the two lags have indicated a clear direction: all statistically significant estimates are positive, which suggest that an increase in previous volatilities increases the following volatility of Nokia A. Nokia ADS seems to exhibit a longer lasting influence on the volatility of Nokia A than itself. Typically, the constant parameter remains insignificant. Significant estimates are *decreasing* on their scale: the more lagged variables that are included into the models, the less are their single influence to explain the variation of Nokia A´s volatility. This is a suggestion that the newest information is the best one in determing volatility behaviour. The third lag is insignificant, thus the lag structure has been restricted to yield two lags. The values of recursively estimated parameters are presented in Tables 30.-32. in the appendix with graphical presentations.

Other model diagnostic statistics have indicated that there are not clear differences between model specifications: for example, the rate of determination remains relatively the same, the models approximately explain 20 per cent of the variations of Nokia A´s volatility during the trading day. Autocorrelations are not present in the models, DW-statistics are near the value of 2. Moreover, descriptive statistics of different model specifications, such as e.g. standard error of regression, sum squared residuals and log likelihood, are just marginally different from each other. Information criteria measures remain almost unchanged and all models are statistically very significant.

As it can be seen in Figures 3.-5. in the appendix, there might have been structural changes. Sudden collapses and jumps in estimates suggest that it would be wise to take into account these changes[55]. Dummy variables might capture such a sudden changes, but using dummy variables in multiple autoregressive processes is a very dangerous and complicated matter. In this sense the dummy variables are excluded in the estimated models. However, a more detailed analysis for the possibility of structural changes is needed, indeed.

The graphical presentations have revealed that the estimates are converging towards zero which suggests that the causality relationships have been vanishing in the course of time. Converging towards zero indicates that the estimates are closing to zero and thus have no explanatory power towards Nokia A´s volatility. This is in accordance with the Granger-causality models with different time spans: it has been found that there are feedback effects between volatility series. Moreover, it has been noticed that increasing lags in dynamic models, the explanatory properties have increased slightly, but the estimates have become insignificant. This suggests that the very recent information is the most relevant in determing other variables` behaviour.

9.5.3. Modelling Nokia´s Volatility including Trading Volumes

The model which includes two lagged terms of Nokia A volatility and one lagged of Nokia ADS volatility has been found to be the best explanation of the variability of Nokia A´s volatility. Thus, a relatively short history of the volatilities can attribute information into explanation of Nokia A´s volatility. That finding is parallel to the results of the Granger-causality analysis, where the shortest lag structures have typically exhibited the most significant levels if there has been revealed significant causalities.

The latest element in recursive estimation extends the trading volume variable. Including the trading volume of Nokia ADS can be justified by means of "hidden" explanatory

[55] Hedvall et al. (1997) have taken into account qualitative factors, such as quarterly earnings announcements, profit warnings and day-of-the-week effects in investigation of price process behaviour on the HeSE and the NYSE.

power. As I have concluded there is rather independence than the evidence of TRADEADS Granger- causing VOLAADS, it can be suspected that the lagged trading volume of Nokia ADS may attribute valuable information in predicting Nokia A´s volatility behaviour. This provides additional motivation to suspect feedback between VOLAA and TRADEADS. Based on these arguments, the model to be estimated can be written as follows

$$VOLAA = \alpha + \sum_{i=1}^{2} \beta_i VOLAA_{t-i} + \gamma_1 VOLAADS_{t-1} + \lambda_1 TRADEADS_{t-1} + \varepsilon_i \tag{34}$$

According to the results, it is clear, that the explanatory power of TRADEADS covers just one trading day. Volatility of Nokia ADS has an explanatory effect parallel to the trading volume series for just one trading day. The intraday volatility of Nokia A extends relevant information up to two trading days. The more detailed results are listed in Tables 33. and in Figures 6. in the appendix.

This chapter has presented some linear dependencies between volatility series. The non-existence of clear and coherent lead-lag structures suggests that there is no information asymmetry within investors or stock markets. The very recent history of the behaviour of the explanatory variables has shown to be the best explanatory modification. Non-linear dynamic models have to be estimated because it can be expected that some variables may non-linearly effect each other. The following chapter concerns this aspect of the dependency relationship of the series.

10. NON-LINEAR DYNAMICS: IMPULSE RESPONSE FUNCTIONS

10.1. The General Presentation of Impulse Response Function

Deeper analysis has been incorporated with impulse-response function (hereafter referred to as IRF). The dynamic volatility-volume relationship has been carried out by simulating the responses of volatility and volume series from the estimated four variables VAR-system. Vector autoregression systems have been proved to be successful for forecasting systems of interrelated time series variables. Vector autoregression has been used frequently, although with considerable controversy, for analysing the dynamic impact of different types of random disturbances on systems of variables. (e.g. Enders 1995, Green 1990, and MicroTSP Online) For an illustrative purpose, the two variable VAR model is introduced. In matrix form

$$\begin{bmatrix} y_t \\ z_t \end{bmatrix} = \begin{bmatrix} a_{10} \\ a_{20} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{20} & a_{22} \end{bmatrix} \begin{bmatrix} y_{t-1} \\ z_{t-1} \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} \tag{35}$$

or with other form

$$\begin{bmatrix} y_t \\ z_t \end{bmatrix} = \begin{bmatrix} \bar{y} \\ \bar{z} \end{bmatrix} + \sum_{i=0}^{\infty} \begin{bmatrix} a_{11} & a_{12} \\ a_{20} & a_{22} \end{bmatrix}^i + \begin{bmatrix} e_{1t-i} \\ e_{2t-i} \end{bmatrix} \tag{36}$$

The matrix (40) express y_t and z_t in terms of the $\{e_{1t}\}$ and $\{e_{2t}\}$ sequences. Enders (1990, p. 294-312) has presented the derivation which yields like (40) but in terms of the $\{\in_{yt}\}$and $\{\in_{zt}\}$ sequences. The vector errors can be written as

$$\begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} = [1/(1-b_{12}b_{21})] + \sum_{i=0}^{\infty} \begin{bmatrix} 1 & -b_{12} \\ -b_{21} & 1 \end{bmatrix} + \begin{bmatrix} \in_{yt} \\ \in_{zt} \end{bmatrix} \tag{37}$$

and combining (40) and (41) forms a matrix

$$\begin{bmatrix} y_t \\ z_t \end{bmatrix} = \begin{bmatrix} \bar{y}_t \\ \bar{z}_t \end{bmatrix} + [1/(1-b_{12}b_{21})] \sum_{i=0}^{\infty} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}^i \begin{bmatrix} 1 & -b_{12} \\ -b_{21} & 1 \end{bmatrix} \begin{bmatrix} \in_{yt} \\ \in_{zt} \end{bmatrix} \tag{38}$$

For the sake of avoiding complexity, defining the 2x2 matrix Φ_i with elements $\Phi_{jk}(i)$ yields

$$\Phi_i = [A_1^i/(1-b_{12}b_{21})] + \sum_{i=0}^{\infty} \begin{bmatrix} 1 & -b_{12} \\ -b_{21} & 1 \end{bmatrix} \tag{39}$$

Equations (40) and (41) can be written in terms of the $\{\in_{yt}\}$and $\{\in_{zt}\}$ sequences:

$$\begin{bmatrix} y_t \\ z_t \end{bmatrix} = \begin{bmatrix} \bar{y}_t \\ \bar{z}_t \end{bmatrix} + \sum_{i=0}^{\infty} \begin{bmatrix} \Phi_{11}(i) & \Phi_{12}(i) \\ \Phi_{21}(i) & \Phi_{22}(i) \end{bmatrix} \begin{bmatrix} \in_{yt-i} \\ \in_{zt-i} \end{bmatrix} \tag{40}$$

and the compactly form yields to

$$x_t = \mu + \sum_{i=0}^{\infty} \Phi_i \in_{t-i} \tag{41}$$

The coefficients of Φ_i can be used to generate the effects of $\in_{yt}$ and $\in_{zt}$ shocks on the entire time parts of the $\{y_t\}$ and $\{z_t\}$ sequences. Each of the four elements $\Phi_{ik}(0)$ are impact multipliers[56]. The accumulated effects of unit impulses in $\in_{yt}$ and/or $\in_{zt}$ can be obtained by summation of the coefficients of the impulse response functions. The cumulated sum of the effects of $\in_{zt}$ on the $\{y_t\}$ sequence in then

$$\sum_{i=0}^{n} \Phi_{12}(i) \tag{42}$$

Plotting the impulse response functions is a practical method to explore *visually* the behaviour of the time series in response to the various stochastic shocks. More detailed properties of VAR modelling and impulse response relation can be obtained in Green, 1990; Hamilton, 1994; and Enders, 1995.

10.2. Vector Autoregression in Impulse Response Procedure

A vector autoregression is a system that takes the form of regressions of each of a set of endogenous variables on lagged values of each of those variables and possibly some exogenous variables. The residuals in a VAR are called *innovations*; they are correlated with each other but uncorrelated with their own lagged values and uncorrelated with the lagged endogenous variables or exogenous variables. If the innovations are not correlated with each other, interpretation is straightforward. The best estimator of each equation in a VAR is ordinary least squares.[57]

Impulse response functions for one innovation measures the effect of a one standard deviation shock today on current and future values of each of the endogenous variables. An impulse response function traces the response of an endogenous variable to a change in one of the innovations. An impulse response function describes the response of an endogenous variable to one of the innovations. Specifically, it traces the effect on current and future values of the endogenous variable of a one standard deviation shock to one of the innovations.

10.3. Model Specification

The four time series, VOLAA VOLAADS, TRADEA and TRADEADS have been regarded as an endogenous variable. There is one impulse response function for each

[56] For interpretation of impact multiplier, see e.g. Enders, 1995, p. 306.

[57] The assumption of the serially noncorrelated disturbances is unrestrictive because any serial correlation could be absorbed by adding more lagged endogenous variables. However, the serial correlation structure has been checked by correlogram with up to 36 lags. None of the four disturbances have exhibited serial correlation.

innovation and each endogenous variable. Thus a 4-variable VAR has 16 impulse response functions. Lag interval has been from one (nearest) to two (farest). Constant term has been used as an optional exogenous variable. The number of trading days after the stochastic shock has been extended to cover ten trading days.

The estimated coefficients of a VAR are very difficult to interpret[58]. In this context, the inference has relied on the visual basis. One graph for each impulse response has been applied to picture single impulse behaviour: the dynamic responses of each variable to 1 standard deviation (positive) innovations in each variable has been investigated. The impulse response functions are presented in Figure 8. in the appendix.

10.4. The Inference of the Responses of Variables to Shocks

10.4.1. Stochastic Shock in VOLAA

First, the responses of four variables to the shock of Nokia A´s volatility have been investigated. The results can be seen from the four IRF plots in the first column in Figure 7. in the appendix. VOLAA reacts strongly negatively to its own shock on day +1 after the stochastic shock. During other days, such as days +2 and +3 the reaction is lighter although clearly negative. This suggest that the volatility shocks happens in a single day, not within days, and do not strengthen the following volatilities. The volatility of Nokia ADS reacts more slightly to the stochastic shock in VOLAA. However, VOLAADS declines on the day following the innovation in Nokia A`s volatility. The reaction is minor on the second day after the shock. After the second day, the negative reaction continues with a slowly decaying rate.

The reaction of VOLAADS is quicker than VOLAA, although the starting point of VOLAA is much higher. This might suggest that the changes in volatility of Nokia ADS react more quickly than Nokia A. One proposal for this is that the investors which are at ADS update their expectations quicker than investors who have a position at Nokia A. All together, the first day after the stochastic shock seems to be the most important in the reaction for the stochastic shock in Nokia A`s volatility.

Both trading volume variables, TRADEA and TRADEADS react negatively to the shock in volatility of Nokia A. An interesting point is the slower decline in the Nokia A trading volume than in Nokia ADS. The reaction of TRADEA covers the first two days to a quite similar extent. On the third day after the shock, the decline continues but on a smaller scale. Where in TRADEA the most reaction is during the two first days after the shock, TRADEADS´s decline is mostly accumulated on the first day after the shock.

10.4.2. Stochastic Shock in VOLAADS

The second phase of impulse response analysis concentrates on exploring the responses of variables to Nokia ADS´s volatility stochastic shocks. The inference is based on the four

[58] Changing the order of equations can dramatically change the impulse responses (MicroTSP Online). Four series create 4! different variations for constructing VAR. In this context, care should be given to interpreting the impulse response functions.

IRF plots in the second column of Figure 7. in the appendix. A positive response of VOLAA can be found on the following day after the shock in Nokia ADS´s volatility. However, after the first day the reaction becomes negative, continuing with a smooth decrease. This is consistent to the spillovers between markets: if VOLAADS faces a positive shock, the volatility of Nokia A faces a positive increase in the following trading day. The spillover effect is consistent with the results of Granger-causality models where it has been concluded that a bi-directional effect exists between volatility series. In contrast to the previous case, the response of VOLAADS to its own shock is negative, which indicates that single day volatility "storms": in the following trading day, the volatility decreases to a strong extent. Parallel to the previous findings during the first day new information or shock is the most important factor within other trading days.

The positive response of trading volume of Nokia A at day +1 can be found with respect to positive shock in VOLAADS. One day after the shock, that is in the second day, the trading volume is decreasing which suggest that the impact of the shock yields just to one trading day. The response in trading volume of Nokia ADS decreases when the stock series has had a positive shock. This relatively smooth reaction may be due to the independence between series of Nokia ADS, as I have suggested in previous chapters. However, the response is a very one-way smooth process and does not indicate rapid reaction to the shock.

10.4.3. Stochastic Shock in TRADEA

Thirdly, it has been explored how responses behave to the shocks in Nokia A´s trading volume changes. The IRF plots are presented in the third column of Figure 7. in the appendix. It is clear that the shock in TRADEA does not cause any significant responses in either volatility series. The IRFs have presented hardly any reaction with respect to the stochastic shock in TREDEA. Negative reaction in TRADEA to its own stochastic shock can be found. The first day after the shock is however the most significant. In this sense, TRADEA´s response indicates decreased trading volume change in the following trading day after the shock. Regarding the trading volume of Nokia ADS, it is evident that the first day after the shock is playing the most important role in reaction to the shock. In the second day after the shock the reaction has increased a little bit but after the second day, the IRF is a very smoothly decreasing process.

10.4.4. Stochastic Shock in TRADEADS

Finally, investigation has been focused on the responses of variables to the stochastic shock of trading volume of Nokia ADS. The IRFs to the shock in trading volume of Nokia ADS are presented in the forth column in Figure 7. in the appendix. It is easily noticed that there are not clear responses of either volatility series to the stochastic shock in TRADEADS, although a marginal increase in reaction of volatility of both series can be seen in the day after the shock. However, it seems like stochastic shock in trading volume does not create any significant responses of volatility variables.

Most of the response of Nokia A´s trading volume is accommodated within the trading day following the shock in trading volume change of Nokia ADS. Responses of TRADEADS to its own shock indicates that trading volume is increasing after the shock. This is also consistent with Nokia A´s trading volume response to its own shock: trading volume changes seem to be very smooth processes on a decreasing scale and additionally share a very similar form of IRFs of their own shocks.

In conclusion, there is clear consistency with the other results concerning the intraday-volatility -trading-volume relationship. The reactions have typically happened within the first days after the shocks. This is consistent with the results of the other estimation procedures: the explanatory properties of the one or two lagged values of the independent variables have shown to be the best explanatory variables. However, it is more than evident that all these econometrical procedures have certain weaknesses and controversial results. In this sense the interpretation should be done with care. The most important results are briefly represented in order to get complete picture of the volatility-volume relationship in the last chapter of this Master`s Thesis.

11. SUMMARY AND CONCLUSIONS

This Master`s Thesis has explored, by means of several econometric procedures and tools, linear and non-linear dependence of intraday volatility and trading volume of Nokia Corporation. Time series from the two stock exchanges have been a good assistance to evaluate lead-lag associations between these variables. In favour of Karpoff (1987), I have found support for positive volatility-volume relationships within each Nokia A and ADS stock series. Approximately a third of the variations of volatility (volume) can be explained by means of trading volume series (volatility) in both stock series. The correlation coefficients among the four series do not suggest very strong absolute correlations, although the correlations are statistically very significant. The difference of volatility series seems to in statistical sense zero, but the correspondent trading volumes are statistically different from zero.

Most of the trading days with highest volatility and trading volume can be explained by means of press releases. This suggests that the investors react quickly to new firm level information. Additionally, the role of "news" has had an effect on updating expectations of Nokia´s future. This unexceptionally brisk trading volume and intraday volatility can be seen as updating expectations about the sights of Nokia`s future. These notices are in favour of Clark (1973). Due to the stationarity of all four series, the standard statistical tools are applicable. Thus, cointegration analysis and error-correction parameters for capturing long-run dependency are not needed in causality investigation. Non-cointegration between variables suggest that the series are unpredictable in the long-run.

Independence between the series of Nokia ADS can be concluded. Feedback or bi-directional Granger-causality between volatility series of Nokia A and ADS is obvious. This is consistent with the findings of Liljeblom (1995) and Hedvall et al. (1997). Trading volume on the HeSE has been found to Granger-cause the corresponding variable in New York, although feedback effects in the total and first subsamples are probable. Interesting results come from the cross-sectional relationships of trading volumes and volatilities. On the one hand, VOLAA Granger- causes TRADEADS, but on the other hand, TRADEA seems to Granger-cause VOLAADS. Confusion of diverse Granger-causalities between volatility and volume series within Nokia A and ADS can be argued by the feedback effects in both cases. Non-existence of very clear causality relationships are in accordance with the simultaneous information hypothesis which suggests that there is not asymmetry information among investors. Based on these findings, predicting a future´s volatility or trading volume is not very worthwhile.

Recursive modelling of Nokia A has revealed the possibility of structural changes. The relatively recent history of the volatility processes convey the most information in determing the Nokia A´s volatility. Additionally, the recursive estimation has produced evidence of zero convergence which suggests vanishing importance of the explanatory variables over the course of time. Evidence of the important role of one lag variable has been produced by including a trading volume variable into model.

Impulse response analysis has revealed very smooth and negative responses for all four variables to their own stochastic shocks. The responses of volatilities to shocks of trading volumes have seemed to have very low response activities. The response of the trading volume of Nokia ADS (Nokia A) to a shock in the trading volume of A (Nokia ADS) has had a clear decrease (increase) after one trading day after the shock. Both responses in volatility and volume of Nokia ADS´s have seemed to exhibit decreasing activity within the day after the shock in Nokia A volatility.

Additionally, the negative response of Nokia ADS´s trading volume has seemed to be accommodated within one trading day after the volatility shock of Nokia ADS. The response of the trading volume of Nokia A has seemed to exhibit the same scale decreasing behaviour within the first two trading days after the shock. In the case of the responses of Nokia A trading volume and volatility, most of the increasing responses have been accommodated within the trading day after the shock in Nokia ADS´s volatility.

In conclusion of the empirical investigation, it has been revealed that one or two lagged values of explanatory variables have provided the most valuable information to explain the variation of the dependent variable. This applies also in IRFs, where the main reactions have accumulated during the first day after the stochastic shock. This suggests that new information is disseminated into prices during the first days. In this sense, new information arrival is an important factor influencing intraday volatility and volume series. Thus, for predicting purposes, the very latest information of time series are probably the most valuable.

In continuing research, it would be interesting to include parts of futures markets. Trading volume and price behaviour in futures markets may be more rational, since it has been suggested that futures markets are more sensitive to new information. However, there are certain weaknesses, such as the relatively modest trading volume of listed corporations, although fast growing, in Finnish futures markets. In this context it would be wise to also include other foreign stock exchanges where Nokia Corporation is listed. Furthermore, event study methodologies regarding dates of annual report releases would be interesting to map investor´s forecast ability. Taking into account "qualitative" factors which may influence the process, as done in Hedvall (1997), will produce new information of dependencies between volatility and volume series.

A challenging task would be an investigation of the volatility and volume dependencies between other telecommunication companies, such as LM Ericsson and Motorola. Also some "new and small" telecommunication companies and mobile phone producers, e.g. Panasonic, Phillips and Sony, might be included into the investigation. From the Finnish point of view, including the "niche" mobile producer Benefon would reveal some interesting departures as has been found by Pursiainen and Viitanen (1996).

Finally, deeper and more sophisticated tools, such as models of time varying variance models, such as applications of the ARCH -family models may be needed to obtain a more exact description and forecastibility of volatility and volume and their relationships. Comparing interday and intraday volatility measures would be interesting to evaluate market reactions to new information among different market places. These aspects of volatility-volume space should be regarded as exciting and fruitful aspects in planning forthcoming research.

APPENDIX

OUTLIER ANALYSIS

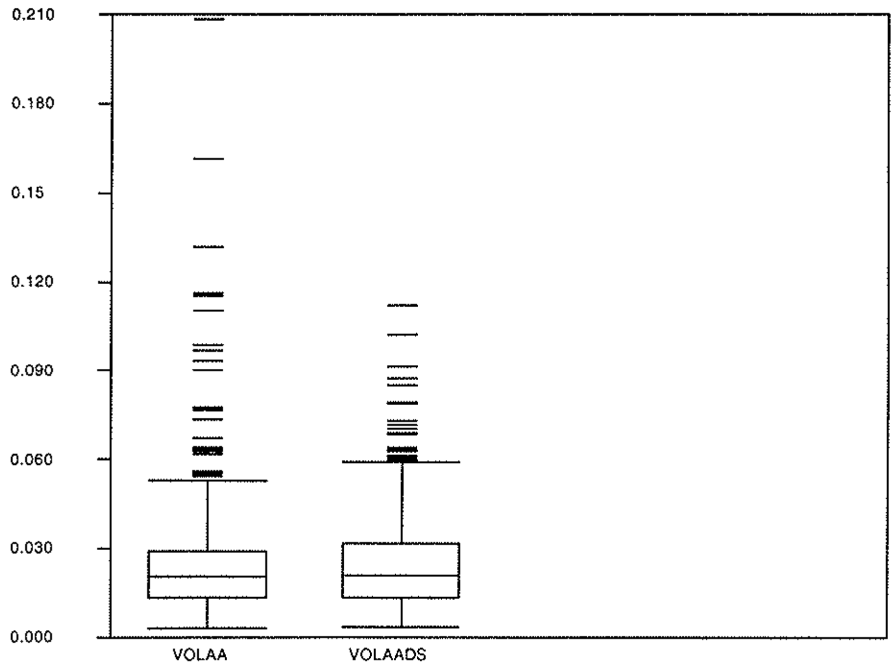

Figure 1. Box-plot. Intraday volatility of A and Nokia ADS.

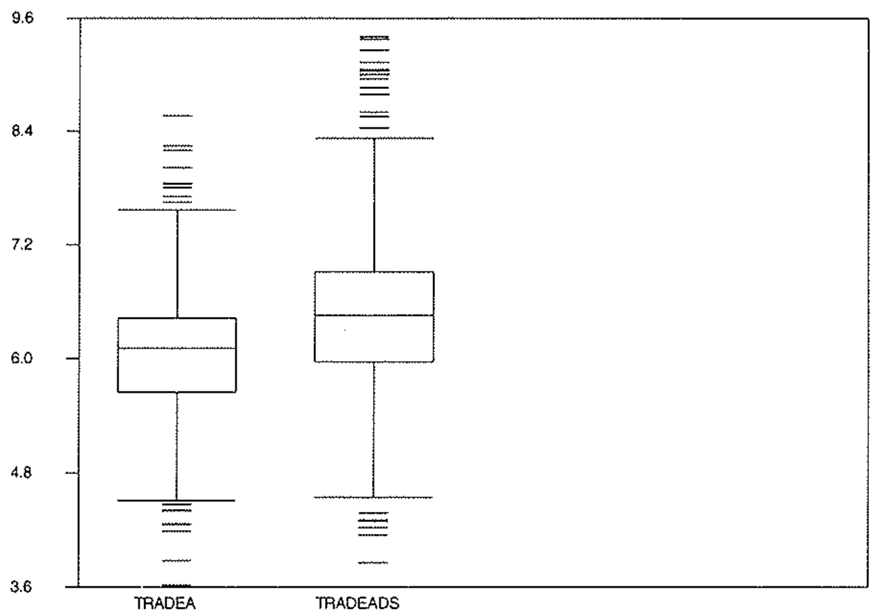

Figure 2. Box-plot. Trading volume of Nokia Nokia A and ADS (in logs).

Table 1. List of highest extreme values of volatility and volume series. (L) and (H) denote low and high observation of each time series, respectively.

Case #	Date	Time Serie(s)	Date of Press Release and Explanation(s)
160	10.03.-95	VOLAA(H) TRADEA(H)	09.03.-95 Nokia extends Globe`s GSM network in the Philippines.
174	30.03.-95	TRADEADS(H)	30.03.-95 Nokia Annual General Meeting: dividend 10 FIM.
175	31.03.-95	TRADEA(L) TRADEADS(H)	30.03.-95 Nokia and E-Plus sign a 800 million DEM contract.
180	07.04.-95	TRADEADS(H)	10.04.-95 Nokia plans new manufacturing site in the US. 10.04.-95 Nokia forms a telecommunication business unit in Canada.
261	11.08.-95	VOLAADS(H)	08.08.-95 Nokia Handsets for APC.
311	23.10.-95	VOLAADS(H)	23.10.-95 Nokia supplies GSM network to China.
327	14.11.-95	VOLAA(H) TRADEADS(H)	16.11.-95 Nokia opens Customer Support and Distribution Centre for South Asia in Singapore.
367	17.01.-96	VOLAADS(H) TRADEADS(H)	16.01.-96 Nokia supplies GSM network to China. 17.01.-96 Nokia establish new product unit for automotive needs; 17.01.-96 Nokia adjusting its television set production.
368	18.01.-96	VOLAADS(H) TRADEA(H)	18.01.-96 Nokia supplies GSM network to China.
385	12.02.-96	VOLAA(H)	13.01.-96 Nokia Research Center to head new EU project. 14.01.-96 Nokia and Cellnet sign GDP 100 million agreement.
420	02.04.-96	VOLAA(H) TRADEA(H)	01.04.-96 Nokia announces first step to withdraw from television business. 02.04.-96 Mr Iiro Viinanen to the board of directors 02.04.-96 Dividend FIM 3.00.
471	20.06.-96	VOLAA(H) VOLAADS(H) TRADEA(H)	19.06.-96 Nokia`s bond targeted to domestic retail investors was issued for FIM 100 million 19.06-96 Nokia to supply GSM network India.
472	24.06.-96	TRADEA(H)	25.06.-96 Nokia to supply GSM network to Poland.

VOLATILITY AND VOLUME DRIVING MODELS

Table 2. Estimated parameters with heteroscedasticity-consistent standard errors and covariance.

	Dependent Variable: TRADEA			
Regressor	**Coefficient**	**Std. Error**	**T-Statistics**	**Probability**
Constant	5.543049	0.04659	118.96530	0.00000 ***
VOLAA	20.79474	1.68637	12.331100	0.00000 ***
R-squared	0.35202	**Mean dependent variable**		6.05145
Adj. R-squared	0.35081	**S.D. dependent variable**		0.66549
S.E.REG.	0.53620	**Akaike info criterion**		-1.24277
S.S.RES.	153.81920	**Schwartz criterion**		-1.22681
Log likelihood	-426.28580	**F-statistic**		290.64060
Durbin-Watson	1.29132	**Probability (F-statistic)**		0.00000 ***
Normality Test	40.3834	**Probability (Jargue-Bera)**		0.00000 ***
ARCH Test	3.02184	**Probability (ARCH-Test)**		0.01063 *

Table 3. Estimated parameters with heteroscedasticity-consistent standard errors and covariance.

	Dependent Variable: TRADEADS			
Regressors	**Coefficient**	**Std. Error**	**T-Statistics**	**Probability**
Constant	5.72943	0.05982	95.78013	0.00000 ***
VOLAADS	29.16222	1.84576	15.79961	0.00000 ***
R-squared	0.30152	**Mean dependent variabl**		6.46005
Adj. R-squared	0.30022	**S.D. dependent variable**		0.86874
S.E.REG.	0.72673	**Akaike info criterion**		-0.63469
S.S.RES.	282.55030	**Schwartz criterion**		-0.61873
Log likelihood	-589.55500	**F-statistic**		230.95210
Durbin-Watson	0.85609	**Probability (F-statistic)**		0.00000 ***
Normality Test	140.30870	**Probability (Jargue-Bera)**		0.00000 ***
ARCH Test	30.12068	**Probability (ARCH-Test)**		0.00000 ***

ANALYSIS OF STATIONARITY

Table 4. Unit root test results of **VOLAA**. *,** and *** indicate statistically significant at 10%, 5% and 1% significance level, respectively. Significancies are based on MacKinnon critical values for rejection of hypothesis of a unit root.

Model Specification	*ADF statistics*	*S.E.REG.*	*S.S.RES.*	*F-stat.*	*Prob.*	*R^2*
In Levels						
with intercept	-3.366358 **	0.017757	0.156705	15.57546	0.0000	0.374229
intercept and trend	-4.157535 ***	0.017671	0.154881	15.23395	0.0000	0.380526
no intercept or trend	-0.929452	0.017926	0.160021	15.56022	0.0000	0.359966
1st Difference						
with intercept	-8.172412 ***	0.017948	0.159772	89.70175	0.0000	0.774580
intercept and trend	-8.160425 ***	0.017966	0.159770	85.04616	0.0000	0.774582
no intercept or trend	-8.178487 ***	0.017931	0.159798	94.85593	0.0000	0.774543
2st Difference						
with intercept	-9.658996 ***	0.019120	0.180958	309.9171	0.0000	0.922455
intercept and trend	-9.644959 ***	0.019138	0.180964	293.8581	0.0000	0.922463
no intercept or trend	-9.669749 ***	0.019102	0.180978	327.7575	0.0000	0.922447

Table 5. Unit root test results of **VOLAADS**. *,** and *** indicate statistically significant at 10%, 5% and 1% significance level, respectively. Significancies are based on MacKinnon critical values for rejection of hypothesis of a unit root.

Model specification	*ADF statistics*	*S.E.REG.*	*S.S.RES.*	*F-stat.*	*Prob.*	*R^2*
In Levels						
with intercept	-2.841124 *	0.014058	0.098221	14.10991	0.0000	0.350402
intercept and trend	-3.209106 *	0.014040	0.097769	13.55380	0.0000	0.353389
no intercept or trend	-0.652350	0.014153	0.099756	14.26841	0.0000	0.340250
1st Difference						
with intercept	-8.138173 ***	0.014183	0.099778	82.75449	0.0000	0.760194
intercept and trend	-8.136375 ***	0.750569	0.099752	78.48516	0.0000	0.760256
no intercept or trend	-8.137637 ***	0.014171	0.099805	87.49717	0.0000	0.760129
2st Difference						
with intercept	-10.31828 ***	0.015069	0.112395	282.7728	0.0000	0.915640
intercept and trend	-10.30361 ***	0.015083	0.112379	268.1340	0.0000	0.915652
no intercept or trend	-10.32932 ***	0.015053	0.112395	299.0847	0.0000	0.915639

Table 6. Unit root test results of **TRADEA**. *,** and *** indicate statistically significant at 10%, 5% and 1% significance level, respectively. Significancies are based on MacKinnon critical values for rejection of hypothesis of a unit root.

Model specification	*ADF statistics*	*S.E.REG.*	*S.S.RES.*	*F-stat.*	*Prob.*	*R^2*
In Levels						
with intercept	-3.729696 ***	0.553125	152.0558	10.59448	0.0000	0.288266
intercept and trend	-4.048636 ***	0.552296	151.2955	10.21961	0.0000	0.291825
no intercept or trend	-0.064628	0.241871	156.3177	10.14574	0.0000	0.268319
1st Difference						
with intercept	-8.397117 ***	0.558970	154.9737	68.71021	0.0000	0.724673
intercept and trend	-8.391403 ***	0.559495	154.9519	65.15574	0.0000	0.724712
no intercept or trend	-8.404586 ***	0.558423	154.9829	72.66772	0.0000	0.724657
2st Difference						
with intercept	-10.40832 ***	0.591657	173.2786	241.6541	0.0000	0.902682
intercept and trend	-10.39292 ***	0.592238	173.2684	229.1225	0.0000	0.902688
no intercept or trend	-10.41881 ***	0.591065	173.2812	255.5903	0.0000	0.902681

Table 7. Unit root test results of **TRADEADS.** *,** and *** indicates statistically significant at 10%, 5% and 1% significance level, respectively. Significancies are based on MacKinnon critical values for rejection of hypothesis of a unit root.

Model specification	*ADF statistics*	*S.E.REG.*	*S.S.RES.*	*F-stat.*	*Prob.*	R^2
In Levels						
with intercept	-3.860365 ***	0.649657	209.7611	8.179375	0.0000	0.238207
intercept and trend	-4.137969 ***	0.648345	208.4944	7.952558	0.0000	0.242807
no intercept or trend	-6.199892 ***	0.658796	216.1382	7.579601	0.0000	0.215047
1st Difference						
with intercept	-8.478904 ***	0.658131	214.8357	57.06910	0.0000	0.686138
intercept and trend	-8.530816 ***	0.658135	214.4051	54.26473	0.0000	0.686767
no intercept or trend	-8.469500 ***	0.657650	214.9545	60.31243	0.0000	0.685950
2st Difference						
with intercept	-10.07823 ***	0.700322	242.7734	201.8329	0.0000	0.885677
intercept and trend	-10.06743 ***	0.700901	242.6836	191.4338	0.0000	0.885719
no intercept or trend	-10.08898 ***	0.699616	242.7734	213.4761	0.0000	0.885677

DESCRIPTIVE STATISTICS OF DIFFERENT TREND REMOVALS

Table 8. Different trend removals of **VOLAA.** MEAN denote original serie subtracted with VOLAA. 1. polyn. denote first order polynominal trend (linear trend). Other variables are calculated similarly.

VOLAA	*Mean*	*1. polyn.*	*2. polyn.*	*3. polyn.*	*4. polyn.*	*5. polyn.*
Average	0.024448	0.024448	0.024448	0.024448	0.024448	0.024448
Median	0.024448	0.024448	0.027111	0.024992	0.025722	0.025103
Variance	4.198009E-32	0.000028	0.000034	0.000043	0.000044	0.000049
Std. deviat.	2.048904E-16	0.005309	0.005820	0.006572	0.006633	0.006993
Std. error	8.841674E-18	0.000229	0.000251	0.000284	0.000286	0.000302
Minimum	0.024448	0.015278	0.009983	0.015156	0.014106	0.013457
Maximum	0.024448	0.033619	0.029753	0.033261	0.032757	0.035054
Co. of var.	8.380532E-13	21.71649	23.80441	26.88274	27.12995	28.60263
Sum	13.12878	13.12878	13.12878	13.12878	13.12878	13.12878

Table 9. Different trend removals of **VOLAADS.** MEAN denote original serie subtracted with VOLAADS. 1. polyn. denote first order polynominal trend (linear trend). Other variables are calculated similarly.

VOLAADS	*Mean*	*1. polyn.*	*2. polyn.*	*3. Polyn.*	*4. polyn.*	*5. polyn.*
Average	0.025054	0.025054	0.025054	0.025054	0.025054	0.025054
Median	0.025054	0.025054	0.027857	0.025841	0.026218	0.024345
Variance	0.025054	0.025019	0.027850	0.025754	0.026127	0.024336
Std. deviat.	1.718807E-33	0.000029	0.000041	0.000050	0.00005	0.000059
St. error	4.14585E-17	0.005353	0.006386	0.007068	0.007106	0.007701
Minimum	1.789066E-18	0.000231	0.000276	0.000305	0.000307	0.000332
Maximum	0.025054	0.015808	0.008073	0.034344	0.034082	0.037323
Co. of var.	1.654779E-13	21.365725	25.487739	28.213031	28.363003	30.73779
Sum	13.453893	13.453893	13.453893	13.453893	13.453893	13.453893

Table 10. Different trend removals of **TRADEA**. MEAN denote original serie subtracted with TRADEA. 1. polyn. denote first order polynominal trend (linear trend). Other variables are calculated similarly.

TRADEA	*Mean*	*1. polyn.*	*2. polyn.*	*3. polyn.*	*4. polyn.*	*5. polyn.*
Average	6.051447	6.051447	6.051447	6.051447	6.051447	6.051447
Median	6.051447	6.051447	6.131482	6.050308	5.966318	5.949876
Variance	1.264532E-29	0.023117	0.028251	0.040896	0.049563	0.050668
Std. deviat.	3.556026E-15	0.152043	0.168081	0.202228	0.222628	0.225095
Std. error	1.534539E-16	0.006561	0.007253	0.008727	0.009607	0.009714
Minimum	6.051447	5.788835	5.629656	5.772015	5.587059	5.54262
Maximum	6.051447	6.314058	6.203557	6.334518	6.426432	6.424627
Co. of var.	5.876324E-14	2.512511	2.777535	3.341805	3.678930	3.719688
Sum	3249.6268	3249.6268	3249.6268	3249.6268	3249.6268	3249.6268

Table 11. Different trend removals of **TRADEADS**. MEAN denote original serie subtracted with TRADEADS. 1. polyn. denote first order polynominal trend (linear trend). Other variables are calculated similarly.

TRADEADS	*Mean*	*1. polyn.*	*2. polyn.*	*3. Polyn.*	*4. Polyn.*	*5. polyn.*
Average	6.460053	6.460053	6.460053	6.460053	6.460053	6.460053
Median	6.460053	6.460053	6.630604	6.63248	6.442934	6.437787
Variance	5.058129E-29	0.101941	0.140824	0.140828	0.203781	0.206235
Std. deviat.	7.112052E-15	0.319283	0.375265	0.375271	0.451421	0.454131
Std. error	3.069077E-16	0.013778	0.016194	0.016194	0.019480	0.019597
Minimum	6.460053	5.908583	5.470525	5.465115	4.726980	4.567345
Maximum	6.460053	7.011524	6.795802	6.793371	7.083377	7.054244
Co. of var.	1.100928E-13	4.942416	5.80901	5.809098	6.987880	7.029835
Sum	3469.0487	3469.0487	3469.0487	3469.0487	3469.0487	3469.0487

GRANGER-CAUSALITY MODELS

Table 12. Granger-causality model. **Observation period 1-537.** *, **, *** denote rejection of the null hypothesis at 5 % , 1 % and 0.1 % significance level, respectively.

	Null Hypothesis: TRADEA does not Granger-cause VOLAA		*Null Hypothesis: VOLAA does not Granger-cause TRADEA*	
Lags	*F-statistic*	*Probability*	*F-statistic*	*Probability*
1	6.45307	0.01136 *	14.6544	0.00014 ***
2	1.76964	0.17140	8.53670	0.00022 ***
3	2.69033	0.04565 *	5.99302	0.00051 ***
4	1.38655	0.23732	4.38658	0.00170 **
5	1.35630	0.23934	3.88945	0.00180 **

Table 13. Granger-causality model. **Observation period 1-268.** *, **, *** denote rejection of the null hypothesis at 5 % , 1 % and 0.1 % significance level, respectively.

	Null Hypothesis: TRADEA does not Granger-cause VOLAA		*Null Hypothesis: VOLAA does not Granger-cause TRADEA*	
Lags	*F-statistic*	*Probability*	*F-statistic*	*Probability*
1	0.20433	0.65162	5.03133	0.02572 *
2	1.47623	0.23040	3.34219	0.03688 *
3	2.39841	0.06846	2.66786	0.04819 *
4	1.33560	0.25714	2.03243	0.09034
5	1.10432	0.35857	1.89621	0.09546

Table 14. Granger-causality model. **Observation period 269-537.** *, **, *** denote rejection of the null hypothesis at 5 % , 1 % and 0.1 % significance level, respectively.

	Null Hypothesis: TRADEA does not Granger-cause VOLAA		*Null Hypothesis: VOLAA does not Granger-cause TRADEA*	
Lags	*F-statistic*	*Probability*	*F-statistic*	*Probability*
1	7.57429	0.00633 **	3.11146	0.07889
2	2.25971	0.10640	2.96588	0.05323
3	2.09543	0.10121	2.78945	0.04106 *
4	1.69859	0.15070	1.99594	0.09555
5	1.47755	0.19750	1.66373	0.14377

Table 15. Granger-causality model. **Observation period 1-537.** *, **, *** denote rejection of the null hypothesis at 5 % , 1 % and 0.1 % significance level, respectively.

	Null Hypothesis: TRADEADS does not Gr. cause VOLAADS		*Null Hypothesis: VOLAADS does not Gr. cause TRADEADS*	
Lags	*F-statistic*	*Probability*	*F-statistic*	*Probability*
1	4.91789	0.02700 *	0.34853	0.55520
2	1.31114	0.27039	0.28191	0.75446
3	1.47080	0.22155	0.20909	0.89011
4	1.40453	0.23117	0.15350	0.96140
5	1.06007	0.38167	0.11087	0.98994

Table 16. Granger-causality model. TRADEADS. **Observation period 1-268.** *, **, *** denote rejection of the null hypothesis at 5 % , 1 % and 0.1 % significance level, respectively.

	Null Hypothesis: TRADEADS does not Gr. cause VOLAADS		*Null Hypothesis: VOLAADS does not Gr. cause TRADEADS*	
Lags	*F-statistic*	*Probability*	*F-statistic*	*Probability*
1	1.14527	0.28552	0.00722	0.93233
2	1.08782	0.33847	0.08149	0.92176
3	1.16012	0.32549	0.81520	0.48645
4	0.93646	0.44332	0.53359	0.71117
5	1.02496	0.40338	0.53112	0.75263

Table 17. Granger-causality model. **Observation period 269-537.** *, **, *** denote rejection of the null hypothesis at 5 % , 1 % and 0.1 % significance level, respectively.

	Null Hypothesis: TRADEADS does not Gr. cause VOLAADS		*Null Hypothesis: VOLAADS does not Gr. cause TRADEADS*	
Lags	*F-statistic*	*Probability*	*F-statistic*	*Probability*
1	1.17833	0.27868	0.05047	0.82242
2	0.56697	0.56793	0.09151	0.91258
3	0.35827	0.78320	0.35075	0.78864
4	0.79180	0.53139	0.33398	0.85496
5	0.56426	0.72737	0.39580	0.85151

Table 18. Granger-causality model. **Observation period 1-537.** *, **, *** denote rejection of the null hypothesis at 5 % , 1 % and 0.1 % significance level, respectively.

	Null Hypothesis: VOLAADS does not Granger-cause VOLAA		*Null Hypothesis: VOLAA does not Granger-cause VOLAADS*	
Lags	*F-statistic*	*Probability*	*F-statistic*	*Probability*
1	14.3245	0.00017 ***	110.578	0.00000 ***
2	9.73510	7.0E-05 ***	51.6539	0.00000 ***
3	8.61445	1.4E-05 ***	31.7402	0.00000 ***
4	5.93183	0.00011 ***	22.2589	0.00000 ***
5	4.21430	0.00092 ***	18.1958	1.2E-16 ***

Table 19. Granger-causality model. **Observation period 1-268.** *, **, *** denote rejection of the null hypothesis at 5 % , 1 % and 0.1 % significance level, respectively.

	Null Hypothesis: VOLAADS does not Granger-cause VOLAA		*Null Hypothesis: VOLAA does not Granger-cause VOLAADS*	
Lags	*F-statistic*	*Probability*	*F-statistic*	*Probability*
1	4.19803	0.04146 *	51.0798	8.7E-12 ***
2	3.85675	0.02235 *	23.3578	4.7E-10 ***
3	3.22203	0.02325 *	15.5623	2.5E-09 ***
4	2.32129	0.05732	11.9183	6.8E-09 ***
5	1.74801	0.12419	10.0363	9.0E-09 ***

Table 20. Granger-causality model. **Observation period 269-537.** *, **, *** denote rejection of the null hypothesis at 5 % , 1 % and 0.1 % significance level, respectively.

	Null Hypothesis: VOLAADS does not Granger-cause VOLAA		*Null Hypothesis: VOLAA does not Granger-cause VOLAADS*	
Lags	*F-statistic*	*Probability*	*F-statistic*	*Probability*
1	3.14371	0.07737	49.8953	1.4E-11 ***
2	2.76679	0.06469	24.5691	1.7E-10 ***
3	3.51275	0.01581 *	14.9827	5.0E-09 ***
4	2.81654	0.02578 *	10.3843	8.1E-08 ***
5	2.24638	0.05026	8.25184	3.0E-07 ***

Table 21. Granger-causality model. **Observation period 1-537**. *, **, *** denote rejection of the null hypothesis at 5 % , 1 % and 0.1 % significance level, respectively.

	Null Hypothesis: TRADEADS does not Gr. cause TRADEA		*Null Hypothesis: TRADEA does not Gr. cause TRADEADS*	
Lags	*F-statistic*	*Probability*	*F-statistic*	*Probability*
1	6.80249	0.00936 **	49.3238	1.7E-12 ***
2	1.47084	0.23067	33.4042	2.2E-14 ***
3	2.19468	0.08774	22.8237	6.6E-14 ***
4	1.13908	0.33721	15.9445	2.5E-12 ***
5	1.01243	0.40955	13.3048	3.2E-12 ***

Table 22. Granger-causality model. **Observation period 1-268**. *, **, *** denote rejection of the null hypothesis at 5 % , 1 % and 0.1 % significance level, respectively.

	Null Hypothesis: TRADEADS does not Gr. cause TRADEA		*Null Hypothesis: TRADEA does not Gr. cause TRADEADS*	
Lags	*F-statistic*	*Probability*	*F-statistic*	*Probability*
1	5.08074	0.02501 *	4.91950	0.02741 *
2	2.71722	0.06793	5.57064	0.00427 **
3	1.97975	0.11743	3.86988	0.00985 **
4	1.43928	0.22144	2.47460	0.04487 *
5	1.38119	0.23178	2.59055	0.02630 *

Table 23. Granger-causality model. **Observation period 269-537**. *, **, *** denote rejection of the null hypothesis at 5 % , 1 % and 0.1 % significance level, respectively.

	Null Hypothesis: TRADEADS does not Gr. cause TRADEA		*Null Hypothesis: TRADEA does not Gr. cause TRADEADS*	
Lags	*F-statistic*	*Probability*	*F-statistic*	*Probability*
1	0.03041	0.86169	67.0292	1.1E-14 ***
2	0.53001	0.58923	40.1304	6.2E-16 ***
3	0.74810	0.52431	27.4759	1.8E-15 ***
4	0.38661	0.81814	19.9263	2.6E-14 ***
5	0.36659	0.87120	16.1113	8.2E-14 ***

Table 24. Granger-causality model. **Observation period 1-537**. *, **, *** denote rejection of the null hypothesis at 5 % , 1 % and 0.1 % significance level, respectively.

	Null Hypothesis: TRADEADS does not Gr. cause VOLAA		*Null Hypothesis: VOLAA does not Gr. cause TRADEADS*	
Lags	*F-statistic*	*Probability*	*F-statistic*	*Probability*
1	10.6394	0.00118 **	80.0054	0.00000 ***
2	2.79656	0.06192	43.1227	0.00000 ***
3	2.40724	0.06639	29.5003	0.00000 ***
4	1.38515	0.23780	21.5630	1.8E-16 ***
5	0.90794	0.47548	17.4577	5.4E-16 ***

Table 25. Granger-causality model. **Observation period 1-268.** *, **, *** denote rejection of the null hypothesis at 5 % , 1 % and 0.1 % significance level, respectively.

	Null Hypothesis: TRADEADS does not Gr. cause VOLAA		*Null Hypothesis: VOLAA does not Gr. cause TRADEADS*	
Lags	*F-statistic*	*Probability*	*F-statistic*	*Probability*
1	3.22705	0.07357	13.5008	0.00029 ***
2	0.61729	0.54019	8.03248	0.00041 ***
3	0.75747	0.51890	5.37737	0.00132 **
4	0.73759	0.56709	3.95155	0.00395 **
5	0.56478	0.72697	3.29549	0.00669 **

Table 26. Granger-causality model. **Observation period 269-537.** *, **, *** denote rejection of the null hypothesis at 5 % , 1 % and 0.1 % significance level, respectively.

	Null Hypothesis: TRADEADS does not Gr. cause VOLAA		*Null Hypothesis: VOLAA does not Gr. cause TRADEADS*	
Lags	*F-statistic*	*Probability*	*F-statistic*	*Probability*
1	2.33047	0.12806	63.4081	5.0E-14 ***
2	0.66703	0.51410	34.6392	4.4E-14 ***
3	0.67459	0.56830	24.2862	6.8E-14 ***
4	0.34133	0.84991	17.9064	5.4E-13 ***
5	0.26725	0.93071	14.2015	2.8E-12 ***

Table 27. Granger-causality model. **Observation period 1-537.** *, **, *** denote rejection of the null hypothesis at 5 % , 1 % and 0.1 % significance level, respectively.

	Null Hypothesis: TRADEA does not Gr. cause VOLAADS		*Null Hypothesis: VOLAADS does not Gr. cause TRADEA*	
Lags	*F-statistic*	*Probability*	*F-statistic*	*Probability*
1	35.9471	3.7E-09 ***	4.90831	0.02715 *
2	16.1885	1.5E-07 ***	2.32577	0.09871
3	10.2897	1.4E-06 ***	1.13859	0.33290
4	7.32727	9.6E-06 ***	0.74260	0.56325
5	6.19829	1.4E-05 ***	0.40501	0.84540

Table 28. Granger-causality model. **Observation period 1-268.** *, **, *** denote rejection of the null hypothesis at 5 % , 1 % and 0.1 % significance level, respectively.

	Null Hypothesis: TRADEA does not Gr. cause VOLAADS		*Null Hypothesis: VOLAADS does not Gr. cause TRADEA*	
Lags	*F-statistic*	*Probability*	*F-statistic*	*Probability*
1	4.83970	0.02868 *	2.02078	0.15634
2	1.85143	0.15907	0.82882	0.43771
3	1.59775	0.19036	0.48176	0.69525
4	1.13757	0.33927	1.05769	0.37802
5	1.40139	0.22421	1.08426	0.36953

Table 29. Granger-causality model. **Observation period 269-537.** *, **, *** denote rejection of the null hypothesis at 5 % , 1 % and 0.1 % significance level, respectively.

	Null Hypothesis: TRADEA does not Gr. cause VOLAADS		*Null Hypothesis: VOLAADS does not Gr. cause TRADEA*	
Lags	*F-statistic*	*Probability*	*F-statistic*	*Probability*
1	29.8430	1.1E-07 ***	0.20660	0.64982
2	16.0909	2.6E-07 ***	0.58979	0.55518
3	9.77037	3.9E-06 ***	0.18916	0.90373
4	7.07800	2.0E-05 ***	0.85671	0.49054
5	5.40240	9.6E-05 ***	0.73851	0.59521

RECURSIVE ESTIMATION

Table 30. Recursively estimated parameters and test diagnostics from the model (33). *, **, and *** denote for rejecting the null hypothesis at 10 %, 5 % and 1 % significance level, respectively.

Dependent Variable: VOLAA				
Variable	*Beta*	*Standard Error*	*T-Statistic*	*Probability*
Constant	3.62E-05	0.000751	0.048244	0.9615
VOLAA_1	0.195854	0.046114	4.247188	0.0000 ***
VOLAADS_1	0.312068	0.053501	5.832924	0.0000 ***

R-squared	0.164883	*Mean dependent variable*	3.41E-05
Adj. R-squared	0.161750	*S.D. dependent variable*	0.018989
S.E.REG.	0.017385	*Akaike info criterion*	-8.098664
S.S.RES.	0.161101	*Schwartz criterion*	-8.074686
Log likelihood	1412.891	*F-statistic*	52.61710
Durbin-Watson	2.097664	*Probability (F-statistic)*	0.000000 ***
Normality		*ARCH(1)*	
Jargue-Bera Test	28201.78	*Engle Test*	0.173418
Probability	0.000000 ***	*Probability*	0.677259
Serial Correlation		*Heteroscedasticity*	
Breusch-Godfrey Test	9.180205	*White Test*	0.802609
Probability	0.002565 **	*Probability*	0.523835

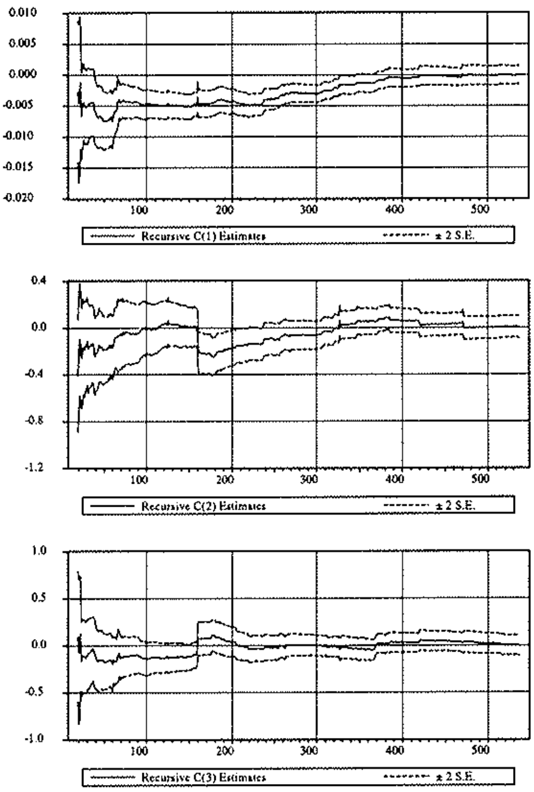

Figure 3. Recursively estimated parameters from the model (33). Lower and upper lines respond ± 2*standard error. C(i) denote i[th] estimator of the estimated model.

Table 31. Recursively estimated parameters and test diagnostics from the model (33). *, **, and *** denote for rejecting the null hypothesis at 10 %, 5 % and 1 % significance level, respectively.

Dependent Variable: VOLAA				
Variable	*Beta*	*Standard Error*	*T-Statistic*	*Probability*
Constant	6.36E-05	0.000746	0.085296	0.9321
VOLAA_1	0.159672	0.047032	3.394925	0.0007***
VOLAA_2	0.131459	0.047172	2.786810	0.0055***
VOLAADS_1	0.269091	0.056606	4.753766	0.0000***
VOLAADS_2	0.038688	0.057512	0.672689	0.5014
R-squared	0.182686	*Mean dependent variable*		4.58E-05
Adj. R-squared	0.176517	*S.D. dependent variable*		0.019005
S.E.REG.	0.017246	*Akaike info criterion*		-8.111048
S.S.RES.	0.157635	*Schwartz criterion*		-8.071027
Log likelihood	1415.573	*F-statistic*		29.61633
Durbin-Watson	2.016296	*Probabilit (F-statistic)*		0.000000 ***
Normality		*ARCH(1)*		
Jargue-Bera Test	31281.05	*Engle Test*		0.030857
Probability	0.000000 ***	*Probability*		0.860626
Serial Correlation		*Heteroscedasticity*		
Breusch-Godfrey Test	1.791435	*White Test*		0.488029
Probability	0.181326	*Probability*		0.864979

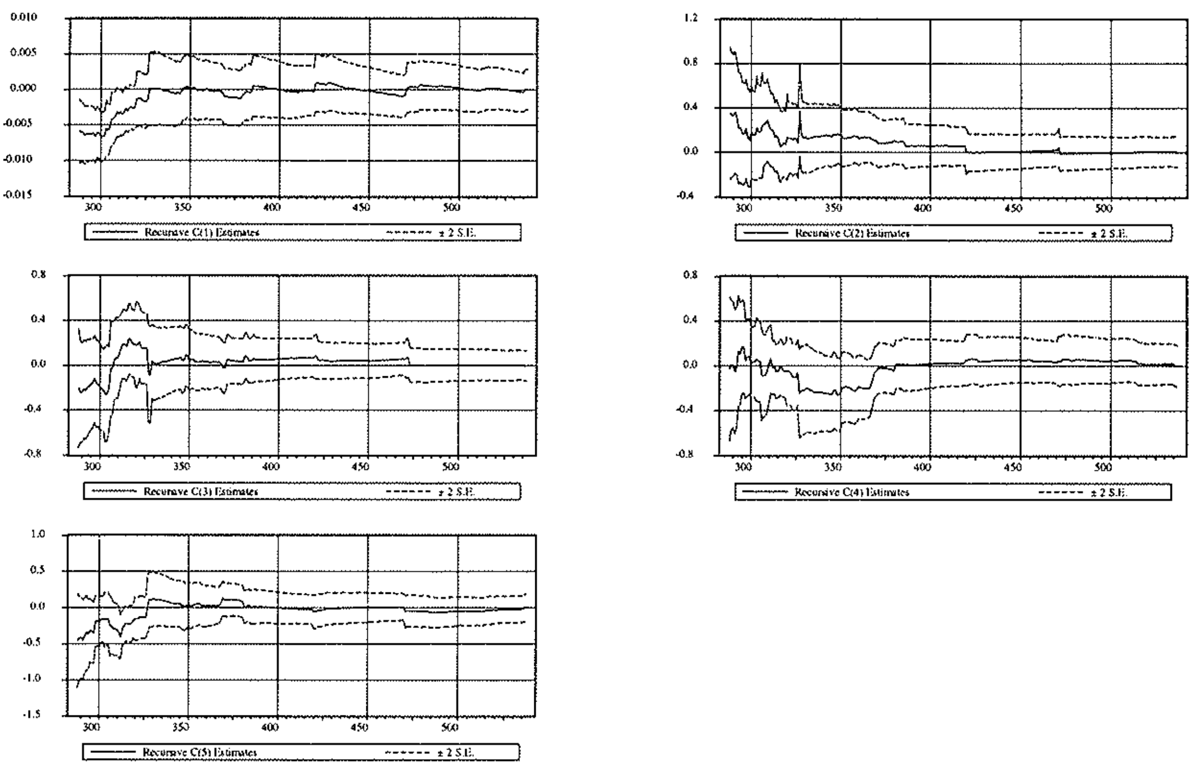

Figure 4. Recursively estimated parameters from the model (33). Lower and upper lines respond ± 2*standard error. C(i) denote ith estimator of the estimated model.

Table 32. Recursively estimated parameters and test diagnostics from the model (33). *, **, and *** denote for rejecting the null hypothesis at 10 %, 5 % and 1 % significance level, respectively.

Dependent Variable: VOLAA				
Variable	*Beta*	*Standard Error*	*T-Statistic*	*Probability*
Constant	7.24E-05	0.000741	0.097669	0.9222
VOLAA_1	0.159834	0.046957	3.403843	0.0007 ***
VOLAA_2	0.109086	0.048023	2.271559	0.0235 **
VOLAA_3	-0.027759	0.047229	-0.587747	0.5570
VOLAADS_1	0.243823	0.056745	4.296814	0.0000 ***
VOLAADS_2	-0.014967	0.059414	-0.251914	0.8012
VOLAADS_3	0.186712	0.057730	3.234216	0.0013 ***

R-squared	0.198807	*Mean dependent variable*	6.92E-05
Adj. R-squared	0.189686	*S.D. dependent variable*	0.019015
S.E.REG.	0.017117	*Akaike info criterion*	-8.122385
S.S.RES.	0.154400	*Schwartz criterion*	-8.066275
Log likelihood	1417.964	*F-statistic*	21.79491
Durbin-Watson	2.027772	*Probability (F-statistic)*	0.000000 ***
Normality		*ARCH(1)*	
Jargue-Bera Test	32158.96	*Engle Test*	0.003807
Probability	0.00000 ***	*Probability*	0.950822
Serial Correlation		*Heteroscedasticity*	
Breusch-Godfrey Test	5.295021	*White Test*	0.436581
Probability	0.021777 **	*Probability*	0.948625

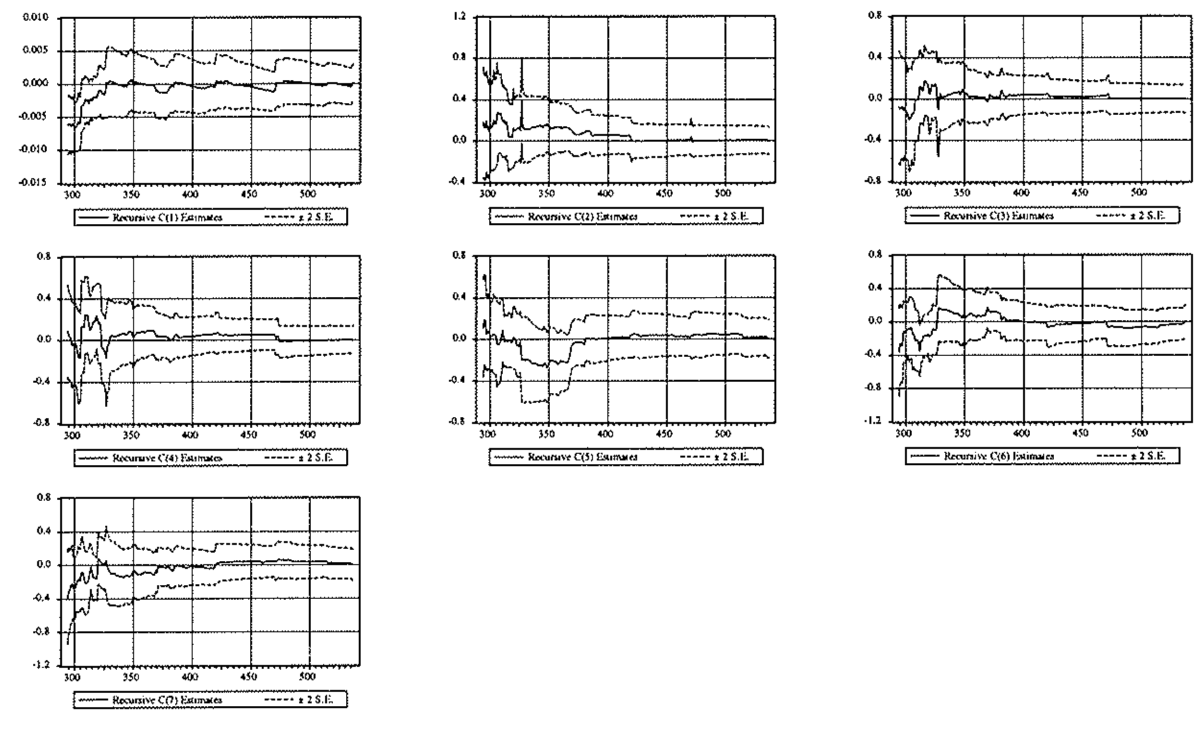

Figure 5. Recursively estimated parameters from the model (33). Lower and upper lines respond ± 2*standard error. C(i) denote i[th] estimator of the estimated model.

Table 33. Recursively estimated parameters and test diagnostics from the model (34). *, **, and *** denote for rejecting the null hypothesis at 10 %, 5 % and 1 % significance level, respectively.

Dependent Variable: VOLAA				
Variable	*Beta*	*Standard Error*	*T-Statistic*	*Probability*
Constant	6.29E-05	0.000745	0.084396	0.9328
VOLAA_1	0.162522	0.046817	3.471425	0.0006 ***
VOLAA_2	0.144314	0.043105	3.347952	0.0009 ***
VOLAADS_1	0.280729	0.053869	5.211292	0.0000 ***

R-squared	0.181988	*Mean dependent variable*	4.58E-05
Adj. R-squared	0.177366	*S.D. dependent variable*	0.019005
S.E.REG.	0.017237	*Akaike info criterion*	-8.113933
S.S.RES.	0.157770	*Schwartz criterion*	-8.081916
Log likelihood	1415.345	*F-statistic*	39.37821
Durbin-Watson	2.021502	*Probability (F-statistic)*	0.000000 ***
Normality		*ARCH(1)*	
Jargue-Bera Test	30748.88	*Engle Test*	0.043910
Probability	0.000000 ***	*Probability*	0.834101
Serial Correlation		*Heteroscedasticity*	
Breusch-Godfrey Test	0.901032	*White Test*	0.502751
Probability	0.342938	*Probability*	0.806421

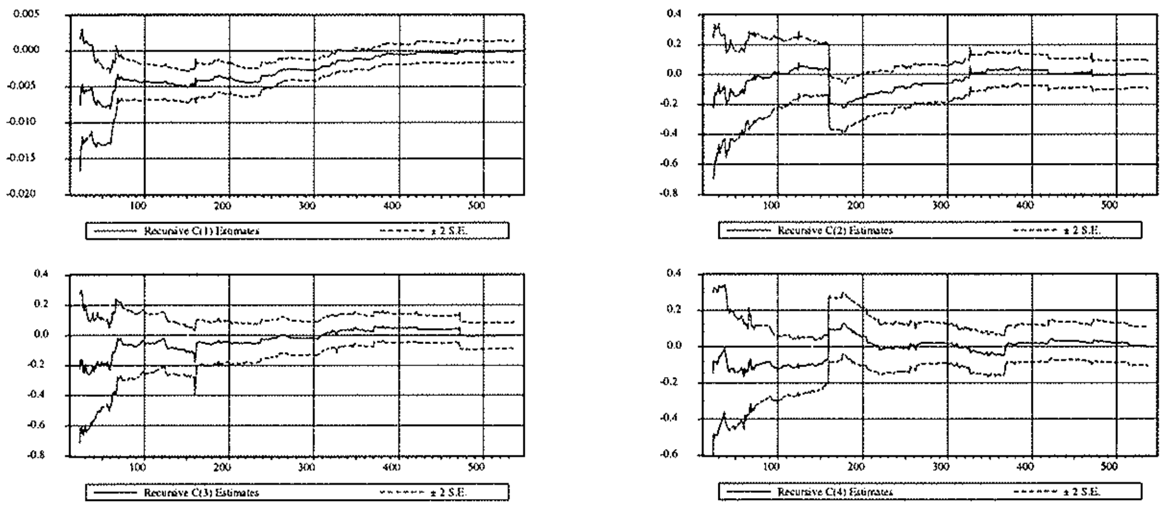

Figure 6. Recursively estimated parameters from the model (34). Lower and upper lines respond ± 2*standard error. C(i) denote i[th] estimator of the estimated model.

Table 33. Recursively estimated parameters and test diagnostics from the model (34). *, **, and *** denote for rejecting the null hypothesis at 10 %, 5 % and 1 % significance level, respectively.

Dependent Variable: VOLAA				
Variable	*Beta*	*Standard Error*	*T-Statistic*	*Probability*
Constant	5.90E-05	0.000743	0.079432	0.9367
VOLAA_1	0.137828	0.047987	2.872227	0.0042
VOLAA_2	0.135123	0.043155	3.131135	0.0018 **
VOLAADS_1	0.230699	0.058314	3.956115	0.0001 ***
TRADEADS_1	0.002334	0.001063	2.195292	0.0286 *

R-squared	0.189359	*Mean dependent variable*	4.58E-05
Adj. R-squared	0.183241	*S.D. dependent variable*	0.019005
S.E.REG.	0.017175	*Akaike info criterion*	-8.119247
S.S.RES.	0.156348	*Schwartz criterion*	-8.079226
Log likelihood	1417.766	*F-statistic*	30.95091
Durbin-Watson	2.013778	*Probability (F-statistic)*	0.000000 ***
Normality		*ARCH(1)*	
Jargue-Bera Test	31140.64	*Engle Test*	0.017260
Probability	0.000000 ***	*Probability*	0.895527
Serial Correlation		*Heteroscedasticity*	
Breusch-Godfrey Test	4.589008	*White Test*	0.442582
Probability	0.015720 *	*Probability*	0.895363

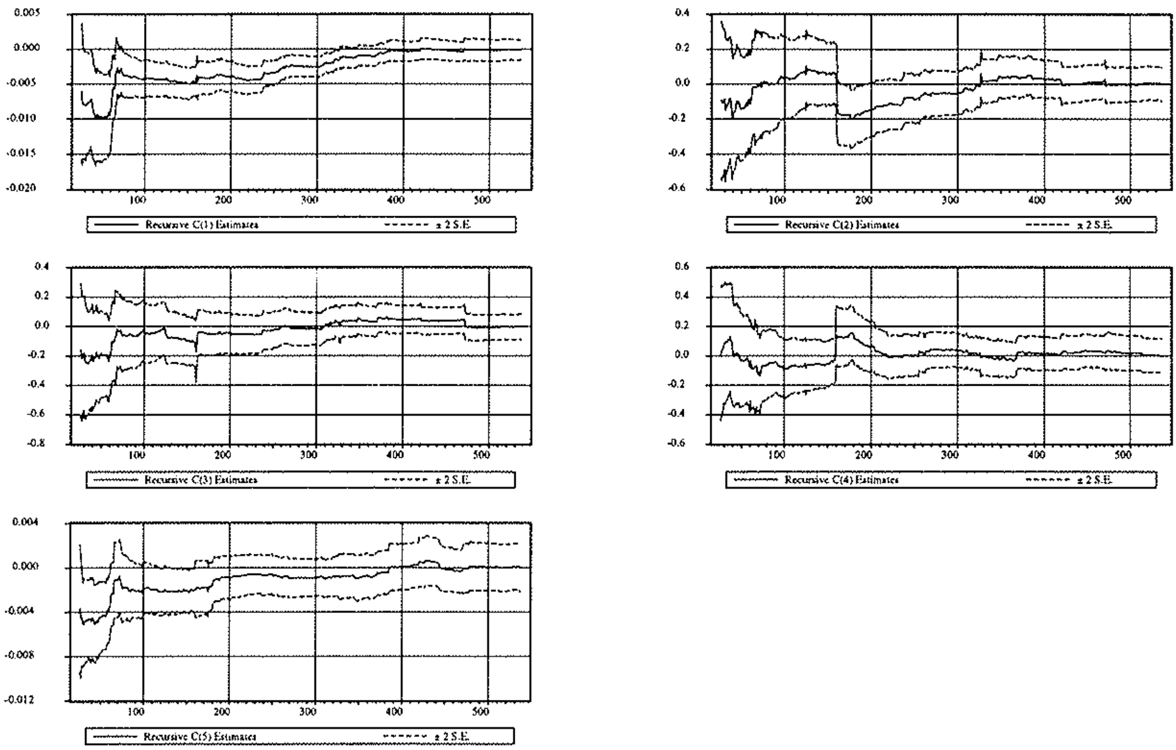

Figure 6. Recursively estimated parameters from the model (34). Lower and upper lines respond ± 2*standard error. C(i) denote i[th] estimator of the estimated model.

IMPULSE RESPONSE FUNCTIONS

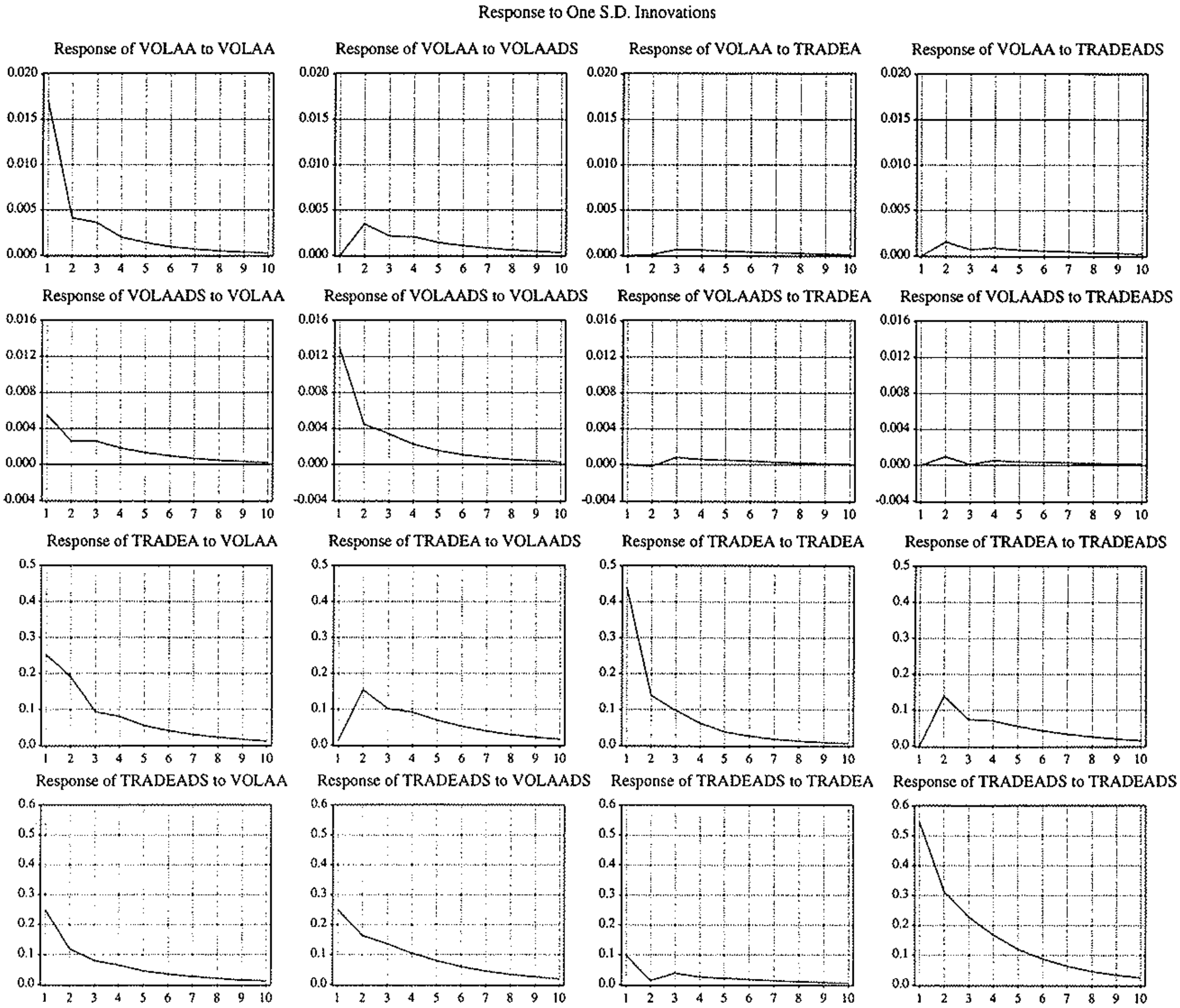

Figure 7. Impulse Response Functions. Number of days after shock in horizontal axisis, in vertical axisis the variable which responds to 1 standard deviation shock of the other variable.

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