Cand.merc. Applied Economics & Finance
Department of Economics
Master's Thesis
August 2010

The Effect of Derivatives Trading on the Underlying Spot Volatility:

Evidence from the Swedish OMXS30 Index and its Component Stocks

$$\sigma_t^2$$

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Characters: 269.558 including 35 tables and figures ≈ 118,5 pages.

Abstract

This thesis examines if derivatives trading activities affect the volatility of the underlying asset. The investigation is conducted on derivatives on the Swedish major index, OMXS30, and on selected components stocks. Based on our theoretical investigation we find that hedgers and speculators use derivatives differently, and that their trading activity can be approximated by trading volume and open interest. Through a number of information hypotheses we find that there is a relation between trading activity, information and volatility. From investigation of previous research and stylized facts of the data, we settle on an ARMA-GJR-GARCH model for our empirical testing. Based on this model we conduct several tests to answer if derivatives trading activity affect the volatility of the underlying asset. The tests are conducted on index- and on asset level. On index level we find that derivatives trading do affect the underlying volatility of the OMXS30. This was documented both over the whole analysed period and in the subperiods. Also, we find significant leverage effect, which corresponds to the results in other research. We also find that speculators' trading activities tend to increase the volatility, while hedgers tend to stabilise the market. Especially shocks from speculators are found large and positive, while the overall effect from trading is negative due to a stabilizing effect from hedgers' trading. Our findings support the Mixture of Distribution Hypothesis and contradict the Dispersion of Believes Hypothesis, and we can thus conclude that some agents affect the underlying volatility more than others. Furthermore, we do not find support for the hypothesis, that derivatives trading activity changes in accordance with the market conditions. On asset level we find a large and positive relation between unexpected shocks from speculators and the underlying volatility, for the whole period. We therefore conclude that derivatives trading do affect the underlying volatility and speculators are the market participants that affect volatility the most.

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1 Introduction and Motivation

1.1 Objective and motivation

Our motivation to investigate how derivatives trading affect the underlying spot volatility in financial markets is found in the aftermath of the recent financial crisis, triggered in the autumn of 2007 by the crash of Lehman Brothers, and the subsequent hefty debate on what effect derivatives had in relation to this failure. The media and some market observers attacked the increasing trading activities in derivatives and financial hybrid products, created from financial engineering, as a major cause of the financial crisis and thus proposed some form of regulation in the area.[1] Conversely, others find that derivatives markets solely create market efficiency and hence find no ground for regulation within the financial sector and derivatives trading.[2] As of 2010 there are still disagreements on what role derivates trading played to build up and trigger the financial crisis and the subject therefore remain controversial in the media. Particularly the recent proposal from the European Commission on how to reform the Over-the-Counter (OtC) derivatives markets within the member countries of the European Union have reignited the debate on this subject.[3] The fact that concerns about the effect of derivatives markets on other financial markets as well as the general economy have existed since the foundation of the Chicago Mercantile Exchange in 1898, does not make the topic less interesting – quite the contrary. During times of crises the debate about derivatives regulation is being reignited, but often forgotten under more stable market conditions. The objective of this thesis is therefore to provide an academic investigation of the effect of derivatives trading on the underlying spot volatility, and the overall resulting effects for the financial markets.

Another motivating factor for this thesis has been the ambiguity in the financial theory about the effect of derivatives trading and the perceived role of the agents on the derivatives markets. By investigating these theoretical issues we seek to establish a link between theory and observed trading activity in derivatives on the Swedish stock market. Also our curiosity to explore and use econometric models plays a major role in this relation.

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[1] Ayadi et al. (2009) and A.Fel'dman (2009)
[2] Liu, Shinhua (2007) pp. 1034-1046
[3] http://www.ft.com/cms/s/0/e8abbc8c-8d22-11df-bad7-00144feab49a.html

1.2 Structure of the thesis

In general we have sought to structure this thesis in a logical and sequential way around the problem statement. The Introduction establishes a good foundation for the structure of the thesis as well as ensuring a clear understanding of thesis' objective. In the following we briefly outline the structure of the thesis.

In section 1 we provide the reader with an introduction and our motivation for investigating the effect of derivatives trading on the underlying spot volatility. We present the problem statement and divide it into three sections that are based on whether we investigate a theoretical problem or we investigate an empirical problem related to the theoretical investigation. We introduce our hypotheses in this section, which will be governing the analysis and investigation throughout the thesis. In general we will structure our thesis around the investigation of the OMXS30 index, which is followed by investigation of individual assets (e.g. first we present the tests we would like to conduct on index level and hereafter on asset level). After presentation of the hypotheses we set up limitations to the scope of the thesis. Section 1 includes an assessment of the academic methodology as a whole, which governs the investigation part of our thesis. Furthermore, in Section 1 we investigate causality, the obtained data, the Swedish stock market and how to select a portfolio of companies for analysis. Lastly, we define various time periods of estimation to investigate whether we can find particular patterns for different types of stock market conditions. The estimation period will among companies differ due the available data for each chosen company included in the analysis.

Section 2 develops the theoretical foundation for the thesis where we investigate the existing financial theory about derivatives trading, the behaviour of different agents in the derivatives markets and how this theoretically affects the price volatility of the underlying spot markets. In this relation it must be noticed that the financial theoretical foundation is ambiguous and does not yield any clear answers whether derivatives trading affect the underlying spot market or not. In this section we also investigate the theoretical link between information flow and asset prices, and how information mitigates from one asset market to another, which is a central feature in interpreting our obtained results in Section 4. We touch upon the general concept of volatility and link it to the former theoretical investigated issues, which also are of significant importance for this thesis. Last in Section 2 we investigate previous research conducted in this field, including the relation to our own problem statement but also with a critical view on the limitations and shortcomings of this research. The amount of previous research on stochastic volatility is found to be very extensive and we therefore attempt to systematize and focus on how to model stochastic volatility in financial markets and exclude methods of modelling stochastic processes from other fields of science.

In section 3 we start out by exploring the statistical properties of the data on both a descriptive level and on basis of statistical tests. We reflect upon the found properties in relation to existing models from the literature review and conclude this section by selecting a preliminary econometric model on basis of previous literature/research and the investigation of the statistical properties of the data. We go into detail with the selected model and analyse the financial - and econometric theory, which lies behind the various components that make up the conditional volatility model of the type ARMA-GJR-GARCH. We apply the Box-Jenkins model specification framework in order to best capture the characteristics of the data for each asset. The non-linearity property of the ARMA-GJR-GARCH model makes Ordinary Least Squares (OLS) estimation biased and incorrect, and we therefore use a type of Maximum Likelihood estimation method that maximizes the desired density distribution. Furthermore, implication and limitations of the chosen model and the estimation method is discussed in this section, as well as our choice of distribution in the estimation procedure. Last in Section 3, in a subsection about competing models, we touch upon other models traditionally used to measure the effect of derivatives trading on the underlying spot volatility.

In Section 4 we present our results for the various hypotheses stated in Section 1, as well as comment upon our findings in relation to the investigated financial -, informational - and econometric theory, our prior expectations and in general. The results will be discussed as they are reported as well as in summations. First we present the results for the tests on index level, which is followed by the results from the tests conducted on single asset level.

In Section 5 we briefly discuss some implications of our results and put them into perspectives of financial markets, the general economy as well as other relevant areas. Furthermore, we suggest possible topics for future research.

Finally, in Section 6 we conclude on our findings in both the theoretical and empirical investigation, and summarize the most important point from our discussion and future implications.

1.3 Problem statement

This thesis is based on three major investigation parts, which each contributes to answering the main problem statement trough investigation of subordinate research questions. The three major parts are respectively, a theoretical investigation, an empirical model specification and an empirical test and results analysis. In the following we first present the main research question. Secondly, we present the sub-questions and objectives associated with each investigation part. This is followed by hypotheses subsection, where the main problem statement is concretised into a number of hypotheses.

The focus area of this thesis is to investigate derivatives trading activities and its relationship with the volatility of the underlying spot markets. In the theoretical investigation we examine how derivatives bring information to the underlying spot markets and how this could have an impact of the volatility of the underlying spot markets. Furthermore, we present a thorough review of the existing research conducted within this area. Based on the results of other researchers we select an ARMA-GJR-GARCH volatility model that includes two explanatory variables for trading activity: volume and open interest, to use in our empirical application. The aim of this is to bring perspectives to the ongoing debate about the role of derivatives in capital markets. Thus, the main research question of this thesis is

Does derivatives trading affect the underlying spot market volatility?

1.3.1 Theoretical investigation

In the theoretical section we provide the theoretical framework and understanding of how derivatives trading might affect volatility of underlying assets. In the first part of the theoretical investigation we look at the unique properties of derivatives trading and how different agents in the derivative markets utilize derivatives for different purposes. We seek to answer the question:

How do different uses of derivatives affect derivatives trading?

Secondly, we explore four theoretical perspectives on the relationship between information and volatility in the market. This provides views on how information is absorbed in the market, at which pace and by which market participants, which is one of the cornerstones in the market microstructure of financial markets. We therefore ask.

Which insights about the relationship between information, trading volume and volatility do various information hypotheses provide?

This will provide knowledge about what should be incorporated in the econometric model for the practical application. The third part reviews the models, methods and findings of previous research within this field. Based on this review and the preceding parts we seek to answer

Based on existence research, which GARCH-type model will best ensure fulfilment of the problem statement?

1.3.2 Empirical model specification

From the theoretical investigation we have found a preliminary GARCH-type model. We investigate the statistical properties of our data and specify a conditional volatility model for each asset's return series. We strive to answer

How does the chosen GARCH-type model capture the characteristics of financial time series data?

1.3.3 Empirical test and result analysis

Based on our theoretical investigation and empirical model specification we have specified a GARCH-type model, which is used to test our hypotheses of the effect of derivatives trading on the underlying spot market volatility. The empirical testing and result analysis consists of a range of regressions as well as coefficient analyses based on the regression results. From this we will answer

Do trading activities in OMX S30 index derivatives have a significant effect on the volatility of OMX S30 Index?

Furthermore, we ask:

Does trading activity in stock options and futures in selected components stocks of the OMXS30 index have significant effect on the volatility of the underlying shares?

1.4 Hypotheses

To investigate the effect of derivatives trading on the underlying spot volatility on the Swedish OMX30 index and on company level we have divided and systemised the problem statement into more specific hypotheses, which enables us to conduct more detailed testing and interpretation of various elements within the research question. First we present our two main hypotheses that relates to the same econometric model and then we extend these hypotheses to include sub-hypotheses in relation to our research questions from the problem statement. The first two presented hypotheses for the OMXS30 index as well as on asset level are general to all the subsequent sub-hypotheses and will always be applied in our testing (an overview of our tests will be presented in the subsequent subsection). For single assets we have been constrained to only test the two main hypotheses due to the characteristics of company specific data. Finally, after each formulated hypothesis we state our prior expectations to the hypothesis, which will be used in the test results analysis. We separate the main hypothesis into two, depending on whether we test on index level (i) or asset level (a).

Thus, our two main hypotheses are: (H_1)

H_{1i}: Trading activities in OMXS30 derivatives will affect the underlying spot volatility of the Swedish OMXS30 index.

H_{1a}: Trading activities in derivatives of component stocks in the OMXS30 index will affect the underlying volatility of these component stocks.

Moreover, our choice of econometric model, where we include variables that proxy for the effect of different types of agents (Hedgers vs. Speculators), enable us to separate the effect from different types of agents in the market. We use daily data for open interests as an approximation for hedging activities and daily trading volume for speculative activities. From the above main hypotheses we thus develop the following two sub-hypotheses, H_2, which can be tested in conjunction with the first hypothesis, H_1, due to the new variables included in our model.

H_{2i}: Trading activity in derivatives on the OMXS30 index from speculators are more destabilizing to the underlying spot volatility than trading activity from hedgers.

H_{2a}: Trading activity in derivatives on component stocks from speculators are more destabilizing to the underlying spot volatility than trading activity from hedgers.

Furthermore, we splitting the trading activities into expected and unexpected components, we are able to measure trading shock from both types of traders. The trading activity split is described more thoroughly in Section 3.

Prior expectations: From our theoretical investigation and review of the previously literature on the subject we expect the volatility and the derivatives trading activities to be positively correlated to some extent. On index level we expect the total number of traded derivatives contracts to have a destabilizing effect on the volatility, which means that an increase in derivatives trading will lead to an increase in the underlying spot volatility. On asset level we expect more ambiguous results due to firm specific characteristics and events, which also might have significant impact on the underlying spot volatility. Most of these events and characteristics are disregarded in this thesis due to the lack of appropriate data and the scope of the problem statement. Regardless of these characteristics we expect a general positive trend between the derivatives trading activities and the underlying spot volatility. Our expectation regarding different kind of traders is the same on both index level and company specific level, where speculators are expected to have a larger effect on the underlying spot volatility than hedgers. Finally, unexpected trading activities from both hedgers and speculators are expected to have a larger effect on the spot volatility for both the OMXS30 index and on a company specific level.

The above two hypotheses are general to all the subsequent hypotheses and will be applied throughout the thesis for every hypothesis. (Cf. later in this subsection where we have systemised all tests in two tables. Here H_1 and H_2 are present for all the tests).

We then investigate whether some types of derivatives have a larger effect on the underlying spot volatility than others. Since our data on index level consists of daily observations of open interest and volume on European put- and call option, forwards and futures, we are able to isolate the effect from each type of derivative. However, forwards and futures are regarded as the one type of asset, as they are not present in Swedish stock market simultaneously; forward contracts trading are replaced with futures trading and thus we merge the two into one data series. For options we summarize puts and calls to get the total picture of the effect on volatility from options trading.

Though we have some asset data consisting of daily observations of open interest and volume on American put- and call options, as well as forward contracts, the data has been too inconsistent and has too many days without trading. Consequently, it has been necessary to leave out the test of how different types of derivatives affect the underlying single share volatility.

We test which type of derivative that predict the spot volatility pattern the best from our main econometric model. Thus, our hypothesis regarding the effect on volatility from different types of derivatives is the following:

H_3: Some types of derivatives have a larger effect on the spot volatility than others

Prior expectations: This hypothesis is only applied on index level where we expect the overall trading activity to have the largest effect on the spot volatility. Furthermore, we expect future- and forward contracts to have the largest effect on volatility due to a significant higher trading volume. This expectation is supported by the characteristics of future- and forward contracts, which in theory should have significant importance due to increased information flow, where they predict price expectations from trading in these derivatives. This is more thoroughly described in our section about information theory.

Derivatives trading have been blamed by many financial spectators to be destabilising for financial markets.[4] Moreover, documented asymmetries in financial time series such as the *leverage-effect*[5] predict an increased volatility during down-turn periods. Thus an interesting angle for investigation would be to divide our testing into specified subperiods based on the market condition. We use the trends on the Swedish stock market, approximated by the OMXS30 index, to select periods of up-turns and down-turns (see Subsection 1.10 for division into subperiods). Finally, we compare with test on the whole period. We thus have the following hypothesis, H_4, about effect on underlying spot volatility from derivatives trading activities at different time periods

H_4: The effect on the underlying spot volatility from derivatives trading activities is dependent on the market condition and changes over time.

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[4] Warren D. Buffet suggested the term “Financial Weapons of Mass Destructions” in his 2002 Chairman’s Letter. www.berkshirehathaway.com/letters/2002pdf.pdf

[5] Black F. (1976) pp. 171 – 188.

Prior expectations: We expect that derivatives trading activities will have a larger impact on the spot volatility during periods with bull-market conditions. We support this expectation with an increased trading activity in derivatives during these times, but recognize the ambiguity imposed by the leverage-effect, where volatility tends to increase during bear-market conditions while the volume tends to decrease. We therefore expect to find less significant results in bear-market conditions than for bull-market conditions.

In the table below we have systemised our tests, where we have listed our hypotheses in column one to get a comprehensive overview. The number assigned to each test will be consistent throughout the thesis and the reader will thus have the ability to go back to the table and use it for look-ups. First we present the test conducted on index level and hereafter the tests conducted on asset level.

Table 1.1. Overview of Index Tests and models employed

Test number	Refered Hypotheses	Level	Instrument(s) used	Period	Econometric model	Effects tested on
Test 1	H1 + H2	Index	Return series	The whole period	GARCH model	GARCH(1,1) processes in the return series
Test 2	H1 + H2	Index	Return series	The whole period	GJR-GARCH model	GARCH(1,1,) processes in the return
Test 3A and 3B	H1 + H2 + H4	Index	All derivatives devided into OI and VOL variables	All periods	ARMA-(GJR)-GARCH model	Total derivates trading Diffent agents Market condition
Test 4	H1 + H2 + H4	Index	All derivatives (ExpectedOI + ExpectedVOL + UnexpectedOI + UnexpectedVOL)	All periods	ARMA-(GJR)-GARCH model	Total derivates trading Diffent agents Shocks from agents Market condition
Test 5	H1 + H2 + H3	Index	All derivatives (optionOI+optionVOL + futuresOI + futuresVOL)	All periods	ARMA-(GJR)-GARCH model	Total derivates trading Diffent agents Types of derivatives

Test 1 and 2 are conducted to find any evidence of leverage effect in the whole period and to select whether a dummy for this effect should be included in the subsequent tests (the GJR element in the models above). Test 1 and 2 also gives us the possibility to evaluate the effect from adding extra variables for trading activities in the following tests. In Test 3 we only include values of lagged open interest and volume to find the overall effect from these variables and to keep our model as simple as possible, while we in Test 4 and 5 include variables for shocks from different agents as well as the effect from different types of derivatives, respectively.

We exclude subperiod tests on asset level as these results have proven to be insignificant. Instead we test the effect from trading activities in the whole period on open interest and volume data in Test 7, while we in Test 8 conduct a test on the effect from trading shocks from different agents in the derivatives market. This is summarized in the table below..

Table 1.2. Overview of Asset Tests and models employed

Test number	Refered Hypothesis	Level	Instrument(s) used	Period	Econometric model	Effects tested on
Test 6	H1 + H2	Asset	Return series	The whole period	GJR-GARCH model	GARCH(1,1) processes in the return series
Test 7	H1 + H2	Asset	All derivatives devided into OI and VOL variables	The whole period	ARMA-(GJR)-GARCH model	Total derivates trading Diffent agents
Test 8	H1 + H2	Asset	All derivatives (ExpectedOI + ExpectedVOL + UnexpectedOI + UnexpectedVOL)	The whole period	ARMA-(GJR)-GARCH model	Total derivates trading Diffent agents Shocks from agents

1.5 Delimitations

We will in this thesis focus on how trading in derivates affect the underlying spot volatility on the Swedish market by using an ARMA-GJR-GARCH model and variations of this model. Evidence from other financial markets are only included in the subsection about previous literature and not included in the empirical investigation. Also competing models (Stochastic Volatility models and Vector Autoregressive Models) are only included in a subsection and not touched further upon since our objective is not to test which of these model that is the best. We leave this part out of the thesis because we do not apply any derivatives trading strategies, which would require superior forecasting capabilities. Instead we use in-sample measures of the conditional mean and variance, which have proven to only differ insignificantly from the three econometric approaches.[6] Also competing GARCH models from other applied situations for measuring the conditional variance are only touched briefly upon in the previous literature section. Testing and

[6] See subsection 2.3

review of all existing GARCH-type models would require extensive work and estimation, which is beyond the scope of this thesis.[7]

On an index level we only test whether European call- and put options and index futures affect the underlying spot volatility. Any other derivatives that might be linked to the investigated index or structured products are not included in this thesis. On the individual stock level we only deal with American put- and call options and futures.

We disregard all company specific events due to the lack of data on this issue and the scope of the problem statement. Thus we only test how derivatives trading activities affect the underlying spot volatility and leave out any other events that might affect the volatility.

We also disregard Over-the-Counter market operations (OtC) and their possible affect on the underlying spot volatility. The OtC market in Swedish index derivatives and stock derivatives are considered to be insignificant in both size and liquidity.[8] Also black pools of trading and other trading pools not announced on the official exchange are disregarded.

1.6 Methodology

1.6.1 Academic methodology

Overall we use an *Inductive* methodology approach in this thesis. In the first theoretical part and in the part where we also investigate previous literature and areas of investigation, the inductive approach is justified from the investigated theories and empirical evidence within the area of the effect of derivatives trading on the underlying spot volatility. Since we find that both empirical evidence and theoretical predictions are ambiguous, we are able to set up hypotheses about these implications. Furthermore, based on the empirical evidence from similar markets we are able to express our prior expectations of our hypotheses.

In the empirical section of the thesis we take a Statistical Inductive methodology approach. This means that we will be able to draw conclusions on whether derivatives trading affect the underlying spot volatility by answer our stated hypotheses by a clear answer. To be able to draw

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[7] Bera & Higgins (1993)
[8] Koivisto and Swedish Riksbank (2004)

these conclusions we use a 95% confidence level for all our testing. We use the found results to draw general conclusions about the effect of derivatives trading on the Swedish stock market.

Finally, in the discussion and perspectives section of the thesis we use a general inductive approach, where we discuss our found results and their implications seen from many opposing angles for both market participants and regulators, respectively.

The data used in this thesis are only quantitative data collected from recognized data providers. We use two data providers – the NasdaqOMX DataStream – and consider both data sources used as highly reliable due to its function for the financial markets and is core business competences within data supply and gathering.

Throughout the thesis we use two examples to illustrate the graphical and numerical characteristics of the data, as well as more thorough test examples. We always present the results and graphical plots for the index data and have chosen to show the plot and results from Electrolux at a company level. The rest of the data on a company specific level have also been investigated to assure consistency in the data results, but will not be presented when no deviations are found. However, for some critical and important graphical plots we have added appendixes for the convenience for the reader. Key test results will naturally be reported for all assets.

In the data analysis part we use both univariate methods where we look at single variables to identify their statistical properties and multivariate models to find the correlation between our investigated variables and find causality (a GARCH type model in our investigation).

1.6.2 Model selection methodology

"The purpose of econometric analysis is to develop mathematical representation of observable phenomena, which we call models or hypotheses"[9]. This means that basically we wish to use statistical models to describe reality; however models remain simplified versions of reality. Thus, the weighing of realism, which usually implies very large and complex models, against parsimony (simplicity), as a general desirable feature of statistical models, will most often be a key parameter in the model selection process. If the model becomes too complex with many

[9] The New Palgrave Dictionary of Economics Online "Model selection" p. 1

explanatory variables it will result in large variances in parameter estimates. Oppositely, a model that is too parsimonious will often carry biases and specification errors in the parameter estimates. Hence, the simplicity that is needed in most models makes models suited for certain tasks, with limitations to those tasks, and should as a consequence be treated as such.[10]

Mathematical models can be divided into two groups, deterministic models and stochastic models. While deterministic models describe an exact relationship amongst a number of variables, such as in e.g. physics, stochastic models describe a statistical relationship between variables. A deterministic relationship is described with certainty while a stochastic relationship is described with probability; hence, stochastic variables have probability distributions.[11] As stochastic processes might not be able to explain an actual time series alone, deterministic variables might be added to the model, such as a deterministic trend variable or a seasonally dummy.[12] The models in this paper, however, will be pure stochastic models, as there are no deterministic processes in our time series data.

A range of features will in general be attractive for most types of models. Such features could be (1) parsimony, for reasons already described, (2) useful for hypothesis testing, (3) that the various components in the model could be interpreted in economic theoretical context and (4) that the model in a satisfactory way represent the observed data. Though all of the features seem important, it might not be the case as the purpose of the model might be more limited or simple. Hence, the most important feature of a model is that it is able to solve the task for which it has been developed in a satisfactory way.[13]

For the present thesis, all of the desirable model features described above have played an important role in the selection of our model. As we set up a range of hypotheses that we wish to test throughout the section of empirical testing, (2) usefulness in hypothesis testing has naturally played a major role in our model selection process. The way in which we have focussed on this feature is mainly throughout an extensive review of existing literature, in which we have been able to sort the vast literature in this field and find the model most appropriate for our type of

[10] The New Palgrave Dictionary of Economics Online “Model selection” pp. 1-2
[11] Gujarati, Damodar N. (2003) p. 22
[12] Lütkepohl, Helmut and Krätzig, Markus (2004) p. 30
[13] The New Palgrave Dictionary of Economics Online “Model selection” pp. 2

hypothesis testing. In the sections of Financial Theory and Information Theory we set up the economic framework, in which the model has to function. That is, we describe (3) how economic theory is linked to the different parameters in the econometric model, directly or indirectly. Furthermore, based on economic theory, we seek to deduce how the model parameters are expected to react under different circumstances. In the subsection Statistical Properties of the Data we analyse the statistical properties of our time series data. This is done with the purpose of selecting the model (4) that best fit the properties of the observed data. The (1) parsimony feature of our model selection is not achieved through an isolated process focussing on that feature but more as a result of the other analysis work combined. However, it should me mentioned that the literature review has played a key role in this process, as it has provided us with knowledge of how to weight complexity and simplicity in these types of models.

1.7 Causality

When analyzing and interpreting regression results a key element is causation, which distinguishes one (or several) variable's causal effect on another variables from barely stating the existence of a dependence relationship between variables. "*A statistical relationship, however strong and however suggestive, can never establish causal connection: our ideas of causation must come from outside statistics, ultimately from some theory or other*"[14]. The topic has not received a great deal of attention in the previous literature about the effect of derivatives trading activity on the spot market volatility. One reason for this could be a general acceptance of the theoretical relation between information flow and volatility, which s described in the subsection on previous literature. Thus, we believe to have provided strong theoretical argumentation for the causal relationship between derivatives trading activity and spot market volatility. To further ensure statistical causality a couple of precautions have been made. First, in models where derivatives trading activity is measured by (total) volume and (total) open interest, that is Test 3, Test 5 and Test 7, the trading activity variables have been lagged one period. The test results have very little difference compared to the results obtained with non-lagged variables; however by lagging the variables we describe a current value by previous observation, thus ensuring a one-way causality. Secondly, in models where open interest and volume are split into expected and unexpected components (Test 4 and Test 8), an ARMA framework of lagged values of the

[14] Kendall and Stuart (1961) p. 279

variables are used to partition volume and open interest into expected/unexpected variables (a more thorough explanation of the procedure is found in the section of model estimation). The fact that the partitioning into expected and unexpected trading are based on previous observations ensures causality in this model by same argumentation as before.

1.8 Data

To account for recognized and known properties of financial time series[15] we use daily observations in both the analysis of the OMXS30 index and on company level. The firm specific data has been collected from both DataStream and provided directly from the data available to the NasdaqOMX.

- Index prices were provided by the NasdaqOMX and consist of average closing prices on the OMXS30 index, which is the leading Swedish share index and a market weighted price index from the 3rd of January 1992 to 17th of May 2010. The OMXS30 index contains the 30 most traded stocks on the Stockholm OMX Exchange and had a market capitalization of 2.415 billion SKR as of the 1st of April 2010.[16] The OMXS30 was listed on the 30th of September 1986 at an index-base of 500 and a 1:4 split was carried through on the 27th of April 1998. All the provided data are adjusted for changes in the index. The long data history ensures consistency in our index data throughout our thesis. The composition of the index is reviewed every half year in December and July, but has remained unchanged for the last 1½ year, which makes the composition quite stable. Adjustment factors are imposed every time changes occur in accordance with the official index methodology[17] and every time changes in the underlying companies' equity composition occur. The index is also adjusted for other events that might affect the price of the underlying companies such as dividends and splits. Derivatives are actively traded on the index on a large scale with a high daily turnover. This fact makes the OMXS30an

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[15] See Section 3.1 where we describe the used data from a statistical point of view

[16] http://nordic.nasdaqomxtrader.com/digitalAssets/66/66284_morning_weight_report_for_omxs30__omx_stockholm_30_index__at_2010-01-04.xls the leading Danish stock index had for comparison a market cap of 742 billion SEK of the 21th of December 2009: http://nordic.nasdaqomxtrader.com/digitalAssets/66/66218_morning_weight_report_for_omxc20__omx_copenhagen_20__at_2009-12-21.xls

[17] https://indexes.nasdaqomx.com/docs/methodology_OMXS30.pdf

appropriate index for investigating the effect of derivatives trading activities on the spot volatility. The current composition of the OMXS30 index can be seen in the table below.

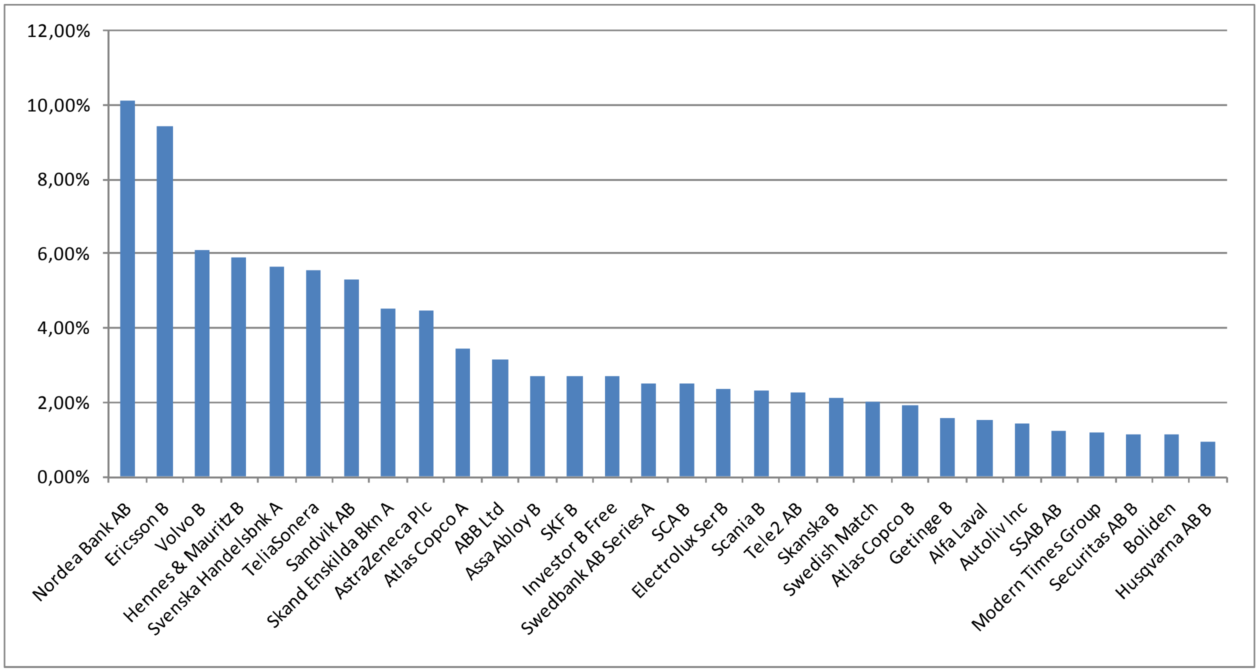
Table 1.3. Companies in the OMXS30 index as of 1st of July 2010

Constituent Name	Weighting	Mkt Cap (SEK) before investability weight	Mkt Cap (SEK) after investability weight	% Weight
Nordea Bank AB	78%	279249,2654	218996,7543	10,13%
Ericsson B	83%	244935,713	204236,6164	9,45%
Volvo B	100%	131879,538	131879,538	6,10%
Hennes & Mauritz B	40%	318572,5632	127429,0253	5,89%
Svenska Handelsbnk A	100%	122508,2885	122508,2885	5,67%
TeliaSonera	50%	239341,3695	119670,6847	5,54%
Sandvik AB	100%	114536,0099	114536,0099	5,30%
Skand Enskilda Bkn A	100%	97445,6906	97445,6906	4,51%
AstraZeneca Plc	100%	96606,92506	96606,92506	4,47%
Atlas Copco A	75%	98712,7344	74034,5508	3,42%
ABB Ltd	100%	68187,18289	68187,18289	3,15%
Assa Abloy B	100%	59022,5734	59022,5734	2,73%
SKF B	100%	58333,21776	58333,21776	2,70%
Investor B Free	100%	58131,087	58131,087	2,69%
Swedbank AB Series A	75%	72517,41893	54388,0642	2,52%
SCA B	100%	54141,21648	54141,21648	2,50%
Electrolux Ser B	100%	51559,78528	51559,78528	2,38%
Scania B	100%	50120	50120	2,32%
Tele2 AB	100%	49328,02435	49328,02435	2,28%
Skanska B	100%	45460,84592	45460,84592	2,10%
Swedish Match	100%	44013	44013	2,04%
Atlas Copco B	100%	41441,25865	41441,25865	1,92%
Getinge B	100%	34469,45971	34469,45971	1,59%
Alfa Laval	75%	44098,70382	33074,02787	1,53%
Autoliv Inc	100%	31431,03659	31431,03659	1,45%
SSAB AB	100%	26652,78236	26652,78236	1,23%
Modern Times Group	100%	25670,33962	25670,33962	1,19%
Securitas AB B	100%	24614,94217	24614,94217	1,14%
Boliden	100%	24219,41402	24219,41402	1,12%
Husqvarna AB B	100%	20293,78341	20293,78341	0,94%

Source: NasdaqOMX - http://nordic.nasdaqomxtrader.com/marketdata/

From the above table it can be seen that the 10 biggest companies in the index account for more than 60% of the index value.

Figure 1.1. Companies in the OMXS30 index as of 1st of July 2010



The total volatility in the index can thus be more affected by changes in these companies.

Daily trading volume and open interest data on an index level are also provided by the NasdaqOMX for both futures, forwards, European put options and European call options. Open interest is the number of derivatives contracts not closed at the end of the day and used to distinguish between hedging and speculative activities. Volume is the total amount of traded contracts per day and used as an approximation of speculative activities.[18] For forward contracts we were provided with data from the 27th of October 1994 to the 22nd of July 2005, while we were provided future contract data from 14th of February 2005 to the 3rd of May 2010. The reason for the overlapping periods for forward- and future contracts is the change in contractual specification of OMXS30 derivatives in 2005. Prior 2005 future contracts on OMXS30 were defined more like forward contracts and were not priced according to the marked-to-market principle. Furthermore, they were only settled at maturity, which is a distinctive characteristic of forwards. Both contract types are despite of these differences priced on basis of the same principle – The Cost of Carry – and we therefore conduct estimation for the whole period.[19]

[18] https://indexes.nasdaqomx.com/data.aspx?IndexSymbol=OMXS30
[19] Nordén (2009); pp. 7 – 8

Derivatives in any overlapping period (often referred to as the transition period of the changed contractual specification[20]) are summarized to avoid any noise or disturbing elements that might affect the underlying spot volatility in this period.

Finally, we compute the return, R_t, on both index level and company level from the log-return formula: $R_t = ln\left(\frac{P_t}{P_{t-1}}\right)$. We also use this measure squared: $R_t^2 = ln\left(\frac{P_t}{P_{t-1}}\right)^2$ any where we calculate and evaluate the standard statistical measure of the return variance.

Daily price observations on a company specific level are collected through DataStream due to the availability of adjusted prices. Open Interests and the number of traded contracts per day are as in the case of the OMXS30 index data provided by the NasdaqOMX. We obtained adjusted prices in the period from the 24th of October 1994 to the 3th of May 2010 for all selected companies (See the following subsection for the selection process of the analyzed companies).

For both the OMXS30 index and on a company level we summarise Open Interest data for options and futures and Volume for options and futures, to get the total effect of derivatives trading on the underlying spot volatility. In a later section we also separate the data into option and future data to isolate the effect of option trading and futures trading, and to find any difference in the effect on the spot volatility from different types of derivatives.

The amount of data for this thesis has been enormous with a total of 298.488 matched observations on a company level consisting of daily prices, volume and open interest. The total number of matched observations on index level was 11.811 daily observations. To handle this amount of information it has been necessary for us to build an ACCESS database, which is the technical foundation of our extensive selection process of analyzed companies. We have used the statistical data program SAS to compute our results presented in the analysis part. To deal with the statistical properties of the data we have been compelled to code the model in SAS (the coding can be found in Appendix 6)

1.9 The Swedish market

In the following we will account for our choice of market in the aspects of market liquidity, market development, and availability of trading activities and data. We will also consider the size

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[20] Nordén (2006), pp. 1 - 4

and structure of the market and taxation issues of special interest for the Swedish derivatives market.

The choice of the Swedish OMXS30 index and its underlying companies as investigated market and securities is an interesting choice in many aspects. The Swedish market is of special interest in the light of derivatives trading and is often viewed as a special case in many empirical studies of the effect of *Security Transaction Taxes (STT)*. These transactions costs was introduced in 1983 as 1% of the value of transactions on assets and derivatives, but abolished in 1993 (prior our analyzed period).[21] As a direct consequence of the imposed STT trading activities mitigated from the Swedish exchange to London Stock Exchange, where Swedish derivatives also are traded. Following the abolishment of STTs the trading activities returned to the Swedish market, which today is seen as the primary market for trading activities in derivatives. This fact is an important feature in our choice of market. Also the high liquidity in derivatives trading on the Swedish market is important in our case, which ensures that sufficient trading takes place to measure the effect on the underlying spot volatility. Finally, we are not aware of any similar investigation on the Swedish market, which makes the objective of this thesis very interesting for both regulators and market participants.

1.10 The selection process for analysed companies

The total number of companies in the OMXS30 index in the analyzed period is found to be 89. Many of these companies have only been included in the index for one period, which makes analysis of these companies irrelevant due to the length of the time series. In the following we will select companies for the analysis that satisfy our selection criteria.

We choose all the companies in the OMXS30 index with more than three years of daily observations. The index is rebalanced every half year where the most illiquid stocks in the index are excluded and the most liquid stocks not in the index are included. Crucial changes in the composition of the index may therefore occur, which we adjust for by ensuring more than three years of continuous observations and inclusion in the index. The number of trading days per year is set to average 252 days (3*252 = 756 observations), which reduce the sample of companies from 89 to 46. This criterion ensures that the chosen companies have sufficient observations to

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[21] Harbermeier & Kirilenko (2003); pp. 87 – 91

detect the statistical properties of the data and to compare the trading activity with other financial times series, which is the main purpose of our testing. To ensure that these companies are liquid enough to find any relation between the trading activity and the spot volatility we impose another selection criteria based on the ratio between the number of days where trading in derivatives occur and the total number of business days in the observation period for each individual company. We use trading in American call options as an approximation for the occurrence of derivatives trading per day and impose a ratio limit of 0.9 to adjust for companies with low trading liquidity in derivatives (Trading-liquidity ratio). When we do this the sample of companies is further reduced to 23 companies (see Table 1.2). The longest observation period is from October 1995 to May 2010 and present for 15 companies. The average number of observations for these 15 companies is 3664 observations, making derivatives in these companies very liquid based on a trading per day basis. The shortest observation period is from February 2006 to May 2010, where we also see a very high trading-liquidity ratio 0,9905 and 1054 observations. The selected companies can be found in the table below.

Table 1.4. Companies for further analysis

Company	Start Date	End Date	Call	Put	Forward	Total # Observations	Trading days in period	Call trading/ Business days
ABB LTD	24-10-1994	03-05-2010	3767	3737	2160	9664	3487,4	0,99329
ASTRAZENECA	24-10-1994	03-05-2010	3894	3894	3125	10915	3912,3	0,99149
ATLAS COPCO A	28-10-1994	03-05-2010	3673	3474	1602	8751	3116,4	0,95463
AUTOLIV SDB	20-06-1995	03-05-2010	3487	3378	1745	8610	2858,1	0,94153
ELECTROLUX B	24-10-1994	03-05-2010	3867	3827	1871	9565	3912,3	0,97999
ERICSSON B	24-10-1994	03-05-2010	3894	3894	3418	11210	3770,2	0,98085
HENNES & MAURITZ B	17-05-1995	03-05-2010	3698	3706	2463	9867	3912,3	0,98842
HOLMEN B	17-02-2000	03-05-2010	2239	1900	549	4688	1780,1	0,96118
INVESTOR B	24-10-1994	03-05-2010	3814	3640	1430	8884	3747,1	0,93059
LUNDIN PETROLEUM	01-04-2005	30-04-2010	1272	1257	804	3333	1337	0,98130
NOKIA CORPORATION	27-06-1996	29-04-2010	3464	3433	2510	9408	3910,2	0,97310
SANDVIK	24-10-1994	30-04-2010	3858	3741	1854	9453	3515,4	0,99021
SCA B	24-10-1994	03-05-2010	3872	3724	1450	9046	3894,1	0,98790
SEB A	24-10-1994	03-05-2010	3879	3828	2042	9749	3910,2	0,98665
SKANSKA B	24-10-1994	07-04-2010	3847	3730	1259	8836	2851,1	0,99646
SKF B	24-10-1994	30-04-2010	3805	3645	1723	9173	3912,3	0,97487
STORA A	24-10-1994	03-05-2010	3763	3600	1648	9011	3909,5	0,93951
STORA ENSO R	30-12-1998	03-05-2010	2691	2570	1304	6565	2480,1	0,99835
SV. HANDELSBANKEN A	01-07-2002	09-04-2010	1943	1839	668	4450	1280,3	0,99352
TELE2 B	09-05-1996	21-04-2010	3481	3401	2322	9204	3912,3	0,96184
TELIASONERA	13-06-2000	16-04-2010	2476	2449	1298	6224	2362,5	0,90540
TRELLEBORG B	24-10-1994	03-05-2010	3834	3738	1746	9318	3912,3	0,98970
VOLVO B	24-10-1994	26-04-2010	3893	3887	2609	10393	3912,3	0,96286

Some of the selected companies have been through major mergers and acquisitions during the analyzed period, which could have affected the trading activity considerably. Of special interest are ABB, AstraZeneca, Nokia and TeliaSonera. In the case of ABB Ltd. the company is listed on three exchanges after the Swedish based Asea AB was merged with the Swiss based BBC Ltd. The Swedish market is seen as the primary market for derivatives trading due to low trading volumes on both the Swiss SIX exchange and on the New York Stock Exchange (NYSE).[22] For TeliaSonera the primary market for derivatives' trading is Stockholm, even though the company is listed both on the Helsinki Exchange and on Stockholm Exchange. Furthermore, the trading in derivatives from the Finish and Swedish exchanges are both administrated by the NasdaqOMX Corporation, which has made it possible for us to attain the total number of derivatives trades for TeliaSonera. For Nokia the primary market is Finland, but again we have been able to collect the total data from the NasdaqOMX

1.11 Division of sub periods for the analysis of both companies and the index

We will in the following explain the reason for each time period we analyze in this thesis.

The whole data period: This is the longest period of matched data (Volume, Open Interest and Prices) available for both the OMXS30 index and on a single stock level. By analyzing this period we will be able to find the overall effect of derivatives trading on the spot volatility.

Periods selected from the state of the Swedish stock market: These periods are divided into upturns and downturns (bull vs. bear markets) on the Swedish markets. We use local maximums and minimums to choose terminal dates. From the below illustration it can be seen that we have identified five periods. We have also added the MSCI World Index exclusive the U.S. market due to its heavy weight in the total international portfolio.[23] Our identified periods from the fluctuations in the OMXS30 index correspond to trend in the world index, which show a clear sign of a high correlation between the Swedish market and the World index.

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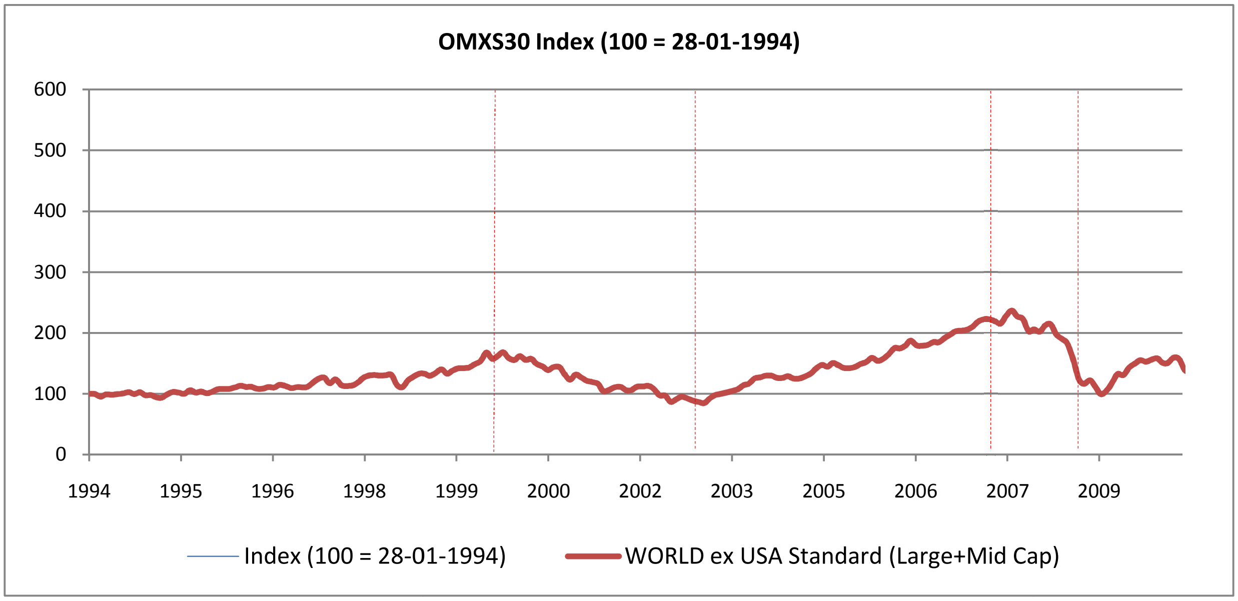
[22] http://www.nyse.com/about/listed/lcddata.html?ticker=ABB & http://www.eurexchange.com/market/statistics/market_statistics/online.html?group=EQU&busdate=20100712&symbol=ABBF

[23] As of September 2009 the US. market counted for 42,41% of the MSCI World Index. We eliminate this heavy weighting by using the MSCI Index World ex. USA. http://www.msci.jp/products/indices/international_equity_indices/acwi-imi/MSCI_ACWI_IMI_Factsheet.pdf

Figure 1.2. Selection of subperiods for further analysis



The below table show the identified periods and standard statistical measures.

Table 1.5. Division of subperiods into Bull/Bear markets

Daily measures	Start of Period	End of Period	Average Return	STD. Deviation	Excess Kurtosis	Skewness	Market condition
Period 1	28-01-1994	07-03-2000	0,107%	1,324%	1,11	0,18	Bull
Period 2	08-03-2000	09-10-2002	-0,199%	2,093%	-2,63	0,17	Bear
Period 3	10-10-2002	16-07-2007	0,095%	1,186%	-0,43	0,14	Bull
Period 4	17-07-2007	05-03-2009	-0,186%	2,289%	-1,23	0,40	Bear
Period 5	06-03-2009	17-05-2010	0,163%	1,547%	-2,30	0,21	Bull

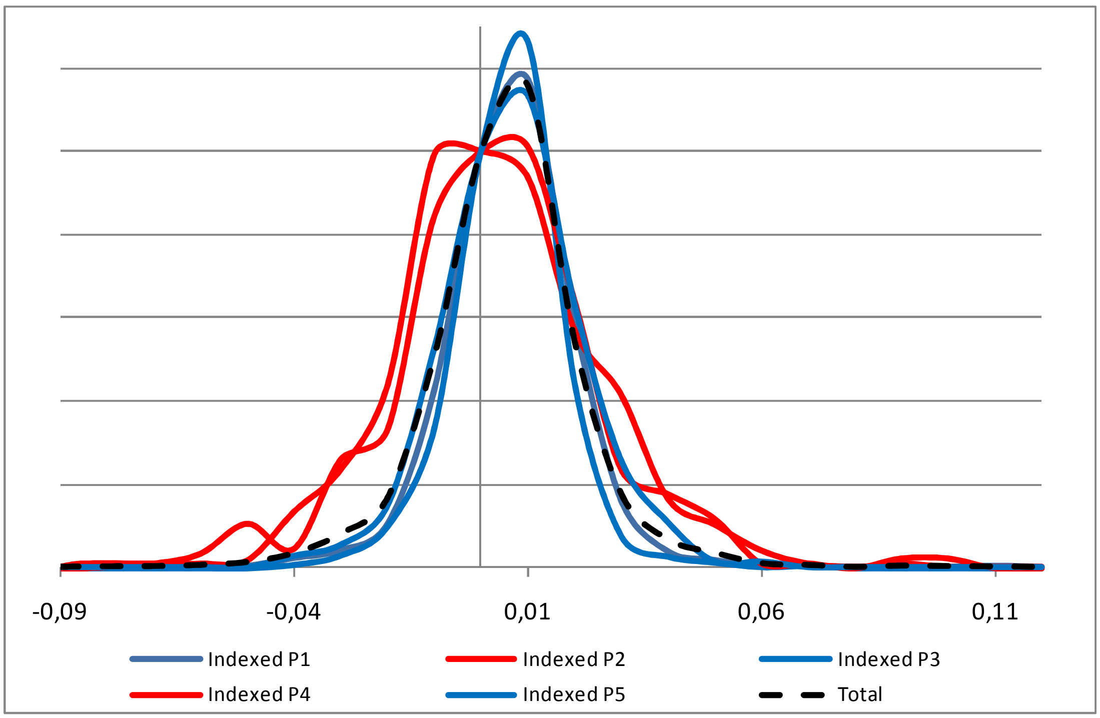
Here we also recognize that the volatility tends to increase in bear-market periods and markets in these times tend to over exaggerate negative news. This asymmetric observation is also known as the *leverage-effect* of stock returns, where negative news in general has a larger effect on volatility than positive news.[24] In sum, this increases the volatility in bear-markets compared to bull-markets. This effect is included in our section on econometric theory, and an integrated part and desired feature of the GJR-GARCH model that include a dummy variable for this stylized fact of financial time series. In the cases where we include the dummy variable in our subperiod

[24] Black F. (1976) pp. 171 – 188. The leverage-effect has its origin from the capital structure of the company. Companies issuing bonds and stocks will experience a decrease in the debt/equity ratio when the stock price goes up. The direct consequence of the decrease is a decrease in the perceived risk of the company, and thus a decrease in the volatility of the company.

testing we will apply rolling periods. To see isolated at one market condition when the dummy is included would not make sense since the GJR element seeks to capture the shocks in downturns measured over the whole period. Including both an upturn period and a downturn period would thus be the most optimal approach in this case (or a stable period as the beginning of Period 1).

Also the distributional properties of the investigated data support the separation in subperiods. From the figure below it can be seen that the return distribution of the OMXS30 index in upturns are different from that in downturns, which we have included in our choice of model.

Figure 1.3. Distributional Properties in subperiods



From the above figure we can observe excess kurtosis in upturn periods, while downturn periods are characterized with left skewness and fatter tails. The total period is observed to exhibit fatter tails and right skewness. These properties are captured by the leverage effect dummy in the GJR-GARCH model.

We apply the same periods for the selected companies when this is possible. In some cases we do not have sufficient data on a company level, and will thus estimate in the available periods.

2 Theoretical framework

In this section we will develop the theoretical foundation on which this thesis is written. The section is divided into three theoretical subsections based on financial theory, information theory and econometric theory, respectively. The first subsection describes the financial theory.

2.1 Financial theory

In this section we review the derivatives and those of their properties that are relevant in the context of this paper. For the empirical investigation of the effect of derivatives trading on the volatility of the underlying asset, we use both futures and options for the investigation on index level as well as on single asset level. However, later in our testing we split the total number of derivatives into futures and option in order to measure their isolated effect on the underlying volatility. Thus, we review financial futures and stock options, their properties and the different types of traders that utilise these derivatives.

2.1.1 Financial futures

Financial futures were introduced to provide an instrument for managing price risk exposure in the financial markets[25]. They are different from other types of futures contracts, such as commodities futures, in a number of ways. First of all, financial futures are not concerned with cost-of-carry or storage cost. This is the price an investor pays for not having to store the underlying asset during the contract period and is part of the price for e.g. a commodities future. Secondly, there is no seasonality in the underlying asset to take into account, which is often relevant for commodities futures based on e.g. farm crops. Thirdly, for financial futures there is no underlying asset that shall be physically delivered in the end of the contract period, only a cash settlement. Finally, because of the high liquidity in most financial assets, the holder of the financial future should not be concerned with the risk of being cornered or squeezed in the underlying assets[26].

Financial futures can be divided into three main groups: interest futures, foreign currency futures and stock market (index) futures, each type of future able to manage risk exposure in their

[25] Reyes, Mario G. (1996), p. 82
[26] Sutcliffe, Charles M. S. (1993), pp. 53-54

respective area[27]. However, the focus of our attention in this paper will be the stock market (index) future.

Properties of financial futures

Transaction cost for trading in stock index futures are in general lower than for trading a corresponding diversified portfolio in shares. Some observers believe that the lower transaction costs are the primary reason for the existence of financial futures[28]. The costs for trading in financial futures are made up of the following elements: commission, bid-ask spread, market impact, opportunity cost of the capital used to paid and maintain margin requirements and possibly taxes.

Part of the reason for the lower bid-ask spread in index futures compared to shares, can be found in the difference in market maker risk exposure in the two types of assets. A market maker in a single or few shares will have a substantial risk exposure to this/these shares following that they cannot hedge the firm specific risk, making them exposed to unsystematic as well as systematic risk. Market makers in index futures markets[29] are less exposed to unsystematic risk as the index future are well diversified in their nature. Furthermore, market makers in single stocks are more prone to be exposed to information based trading than market makers in index futures. If an investor has access to information that is not reflected in the market price, it is more likely that the information regards a single stock rather than the entire index. Because of the additional risk, from carrying a less diversification inventory and adverse information, the market maker in a single or few stocks will quote larger bid-ask spreads than the market makers of stock index futures[30].

Another significant determinant of the low bid-ask spread for stock index futures has been the high volume of futures trading. It has been found that as daily volume goes up, the bid-ask spread decreases.[31].

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[27] Sutcliffe, Charles M. S. (1993), p. 53
[28] Kling, Arnold (1986), pp. 41-54
[29] Scalpers: Definition
[30] Rubinstein, Mark (1989), pp. 20-20
[31] Followill & Rodrigues (1991) pp. 1-11

Financial futures represent a geared position in the market. The investor does only need funds for the initial margin plus the money he needs to maintain the margin over the contract period. The low initial investment coupled with the same exposure as the underlying asset, which have a much larger initial investment, results in a high leverage compared to the underlying asset.

2.1.2 Stock options

In many ways financial futures and options are very similar as both types of derivatives are concerned with buying/selling a financial asset at some point in the future. The main difference is that the future contract involves the obligation to buy/sell an asset in the future, whereas the option gives the holder the right but not the obligation to buy/sell the asset. This characteristic has the effect that an initial payment is necessary when entering an option contract; otherwise the option right to buy/sell would be free. Oppositely, a futures contract can be free of charge when agreed upon as a cash settlement will take place at the end of the contract period.

Like futures there exists a range of different option with different types of underlying assets such as stock indexes and currencies. However, in this paper we will only use options in the context of stock index and single assets, namely individual stocks.

Properties of stock options

Similar to futures it is often cheaper to trade in options than in the respective underlying asset because of the lower transaction cost associated with stock options (an exception is when an investor wish exposure towards a stock over a longer period. With a stock option he will need to repurchase an option at the end of the period, which carries additional transaction cost. By holding the stock the "contract" is potentially indefinite). Because of the lower price but the same risk exposure, the option is relatively more volatile than the underlying asset and hence gives the investor more price action per dollar invested than if he had invested in the underlying stock. Moreover, for the investor stock options may have some advantages over stocks with respect to e.g. taxation and stock market restrictions because option markets often have their own institutional rules and regulation. Difference in the rules and regulation for stocks and stock options may motivate option trading. An example is short selling, which is often a restricted procedure in regular stock markets. However, by using options contracts the investor can replicate a stock short sale but without being subject to the stock market restrictions on short sales[32].

2.1.3 Derivatives traders

The traders in financial derivatives go beyond risk managers and a major reason for the success of derivatives markets is its attractiveness for many different types of traders. We have divided the traders into three groups: hedgers, speculators and arbitrageurs. In the following we describe the three different types of traders and their use of financial derivatives.

Hedgers are traders who use financial derivatives to manage their risk exposure. If an investor wants to secure his stock investment and neutralise the risk associated with price movements, he can lock the price at a specified time in the future by selling futures contracts that agree on delivery of assets similar to his investment at a specified time. This use of financial futures is comparable to the traditional use of commodities futures that were developed to manage price change risk in the commodities market. In case the investor is concerned with the possibility of a decline in a share price within the next months, he can protect his investment by buying put options with an exercise price equal to his lowest acceptable price level. This gives the investor an insurance against the risk of the stock falling below an unacceptable price level, while still maintaining the upside potential of the stock.

The fundamental difference between hedging with futures and hedging with options is that futures neutralise risk and price movements by fixing the price at a specified level. Stock options, on the other hand, provide insurance as they protect the investor from undesirable price movements while maintaining the possibility of favourable price movements[33].

Additionally, derivatives such as futures contracts are often for investment/portfolio management. Though this type of use is different from hedging, it falls within the same group in this context. This is due to the fact that both hedgers and investment managers use derivatives in combination with other assets to control their combined risk/exposure. Furthermore, both hedgers and investment managers will normally hold derivatives for a longer period than e.g. speculators.

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[32] Kolb, Robert W. (2003) pp. 311-312
[33] Hull, John C. (2009) pp. 10-11

Because of the favourable properties of futures, such as low transaction cost and liquidity, a portfolio manager will sometimes use futures contracts to control the beta of his portfolio. The beta of a portfolio is the weighted sum of the asset betas in the portfolio. Traditionally there are three ways in which a portfolio manager will try to control the portfolio beta: trading shares, borrow/lend at the risk free rate to trade shares (CAPM framework) and using stock index futures. The two first methods both involve trading shares and hence have potential large transaction cost as well as compromising diversification. Index futures, on the other hand, has relatively low transaction cost, low initial investment (margin payment) and is a very simple way to adjust beta by buying/selling index futures without compromising diversification. Thus, index futures will often be a preferred tool for controlling beta[34].

Speculators, in contrast to hedgers, wish to take a position in the market by using derivatives, which is comparable to betting on the market/stock is either going up or down. The difference compared to a similar stock investment lies in the leverage effect where derivatives speculators only will have to pay the options price or futures margin requirement to get the same asset exposure as the underlying asset. Thus, good outcomes becomes very good and bad outcomes becomes very poor/looses the entire investment. The possibility of high exposure for a relatively small initial investment is a major cause of the popularity of derivatives trading. Another feature of speculative trading is that it is often performed by 'day traders' who only hold the asset within the opening hours the exchange.

Though futures and options are similar in that they provide the speculator with a leveraged instrument they have a fundamental difference. Namely, for stock options the downside is limited to the initial investment, whereas for futures contracts it is potentially unlimited[35].

Arbitrageurs are a third group of traders who participates in derivatives markets. The concept of arbitrage involves locking in a risk free profit by exploiting mispriced asset in two different markets, either in terms of asset type of geography. E.g. there might be a mismatch between the price of a futures contract and the price of the underlying asset. Similarly, a stock listed on

[34] Elton , Edwin J. et al (2007), pp. 623-627, Sutcliffe, Charles M.S. (1993), pp. 271-277
[35] Hull, John C. (2009) pp.11-14

different exchanges with different currencies might not be completely in line with the current exchange rate. Both examples could create a risk free profit for an arbitrageur.

Such arbitrage opportunities cannot last for long as the arbitrageurs' exploitation will change the asset's supply and demand until they match the futures-/spot price relationship or current exchange rate. Following this, the existence of arbitrageurs cause arbitrage opportunities to be kept at a minimum as possible disparities will quickly be exploited and hence corrected for[36].

As the effect of arbitrageurs is difficult to measure, they are of less importance for this thesis. Moreover, as the speed and efficiency of financial markets are increasing, the effect from arbitrageurs is getting less significant. Thus, throughout the rest of the thesis, we will only refer to the effect from hedgers and speculators.

In the preceding we have reviewed three groups of derivatives traders: hedgers, speculators and arbitrageurs, though arbitrageurs are of minor significance for this thesis and will not be used throughout the rest of the thesis. Each group have their own motive for trading derivatives. Furthermore, they have different trading patterns, such as holding period, which reflect their intention with trading derivatives. For our empirical investigation this difference in holding period plays an important role in identifying different types of investors and will ultimately aid in explaining if/how derivative trading activity affects volatility of the underlying assets. *Open interest measures are pertinent for at least two reasons. First, since many speculators are "day traders" who do not hold open positions overnight, open interest as of the close of trading likely reflects primarily hedging activity and, thus, proxies for the amount of uninformed trading. Using open interest in conjunction with volume data may provide insights into the price effects of market activity generated by informed versus uninformed traders or hedgers versus speculators*[37]. How trading activity by different investor types affects volatility and how this is reflected in our empirical model, is described thoroughly in Section 3.

2.2 Information theory

While we in the preceding section discussed the general function of derivatives markets, we will in the following describe the theoretical implications for the underlying spot markets. We will in

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[36] Hull, John C. (2009) pp.14-15

[37] Bessembinder, Hendrik & Seguin, Paul J. (1993) p. 25

the first section discuss the concept of volatility to get an in-depth understanding of this term, which is a key concept in our thesis.

2.2.1 The concept of volatility

For practical reasons we define the concept of volatility in the following due to its many interpretations and its importance for derivatives markets – both for pricing issues and return forecasting. Furthermore, our definition of volatility governs the choice of model in a later section. We will not touch upon volatility measures not included in this section.

In our analysis we consider two main volatility measures to evaluate the relation between trading activities in derivatives and the volatility of the underlying assets.

Actual Historical Volatility is the conventional statistical measure for the variance in asset returns, which is well defined and used throughout the financial literature. We only use the Actual Historical Volatility in our preliminary examination of the data together with other standard statistical measures. The measure has limitations and fails to explain any relation between different times series. Its main feature is the intuitive statistical interpretation, and we define it as:

$$\sigma_t^2 = \frac{\sum_{i=1}^{N}(r_{t-1} - \mu)^2}{N - 1}$$

To find any relation between our investigated times series we conduct the conditional variance from our econometric model (see Section 3), which is also defined as the stochastic volatility. The main feature of the found conditional variance is the decomposition into fundamental volatility and transitory noise (Approximated by volume and Open Interest data). This allows us to conclude whether the conditional variance is caused by noise trading by speculators or is a more complex function of more factors. In this terminology Total Volatility has been interpreted as the sum of fundamental volatility caused by information arrival that follows a random walk path (Stochastic process) and transitory noise caused by speculators trading activities. Thus we have the following expression for the total volatility:[38]

$$TV = GARCH\ component + Noise$$

[38] Hwang & Satchell (1999), pp. 762 – 765. For a more in depth description of our econometric model see Section 3

By dividing the conditional variance into an unobservable component and the effect from noise trading gives us the possibility to test the influence of speculators on the volatility. From the level of significance of these we are then able to conclude whether trading activity in derivatives have any stabilizing or destabilizing effects on the underlying volatility, and how big the behavioural finance element in the pricing process is. Also, we will not touch upon *Implied Volatilities* due to its relation to option pricing models, which are distinctive different from both Stochastic Volatility Models and GARCH models.

The inclusions of lagged returns, trading volume and volatilities in our model also have some desirable statistical properties, and the conditional variance is therefore a total measure of both the above-defined total volatility and other factors. In this relation we leave out all other factors that might influence the volatility due to lack of data such as macroeconomic announcements or events. We will return to other factors that might affect the conditional volatility in the discussion of the model and the interpretation of our results.

2.2.2 Information flows & price volatility

The theoretical investigations of volume, the function of derivatives markets and spot market volatility are intertwined and contain many of the same issues. In the following we use the framework presented by Ross (1989) to establish the link between Information Flow and asset price volatility. This framework is hereafter used in connection with different information hypotheses and the Efficient Market Hypothesis (EMH), where we also address the relation between Volume and Volatility from a theoretical perspective. This is a good stating point for the subsequent section where the data used is analyzed and the model is interpreted.

2.2.3 The theoretical relation between Information flow and Volatility

The link between information flow and asset price volatility has often been omitted in empirical investigations on the effect of derivatives trading on the underlying spot market.[39] The direct consequence of this exclusion has resulted in misinterpretations of some empirical evidence of increased or decreased volatility, which in some cases have served as basis for regulatory initiatives on the derivatives markets. We will investigate these issues to be able to draw the right conclusions in our analysis and for the interpretation of our model.

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[39] Mallikarjunappa & Afsal (2008). pp. 63. & Antoniou (1995), pp. 119.

The link between the future markets and its affect on the available information to the market participants has its point of departure at the examination of the relation between information and spot prices. The theoretical investigation in this relation comes up with at least two reasons for why the introduction of derivatives markets alters the information flow, which has an effect on the underlying spot markets.[40] 1) Futures trading attract speculators as an additional set of traders who trade on future expectation and information about assets. These expectations are incorporated in the spot prices as the speculators revile them in their trading behaviour. In addition, even though speculators are blamed to destabilize markets they are still critical for the existence and efficiency of the financial system. The presence of speculators makes it possible for hedgers to transfer their risk through the holdings and demand of the speculators, which is the most important property of the derivatives markets. 2) A reduction in transaction costs from the introduction of derivatives markets reduces the dispersion of expectations of the market participants due to a higher liquidity, and information is thereby revealed at an increased rate. The latter is documented in several investigations as the lead-lag relationship between stocks and stock index futures.[41] A more theoretical linkage would be to investigate the relationship between the variance in the information flow and variance in spot prices. In an arbitrage free economy this scenario would mean that $\sigma_I^2 = \sigma_P^2$, which is Ross' Theorem 2 that states, *"The variance of price change equals the rate of information flow"*[42](a formal proof can be found in Appendix 1) and assume that asset prices are a martingale.[43] This simplification means that prices one day are independent of prices the previous day, and that asset prices reflect all available information (the prices reflect an information process), hence supporting the *Efficient Market Hypothesis* in its strongest form. It also states that information flow one day is independent of information flow the previous day. Hence, if the introduction of derivatives changes the information flow to the market, the volatility of the spot market will also change. In contrast, if arbitrage possibilities are present the relation can be expressed as: $\sigma_P^2 \neq \sigma_I^2$, and variances in the information flow from the introduction of futures markets do not fully explain the volatility of the spot markets.

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[40] Cox (1976), pp. 1.217 – 1.218 & Antoniou (1995), pp. 119.
[41] Kawaller (1987) pp. 1.312 – 1.313 & Chen (1992) pp. 126 – 128.
[42] Ross (1989), pp. 7.
[43] A discrete-time martingale is defined as: "In probability theory, a martingale satisfies the following, E(X_{n+1}|X_1,...,X_n)= X_n, where X_1,...,X_n are a sequence of random variables. In other words, the conditional expectation of X_{n+1}, given with all past observations, only depends on the immediate previous observation." http://hea-www.harvard.edu/AstroStat/statjargon.html

Theorem 2 is often associated with the two information hypotheses, The Mixture of Distribution Hypothesis (MDH) and the Sequential Information Arrival Hypothesis (SIAH), which we will deal with in Subsection 2.2. An underlying assumption for the above two information hypotheses is that the increased information flow reveals information that alters the distribution of cash flow from the asset. This obviously changes the asset value and is an important assumption in Ross' theorems. Furthermore, Ross establish a relation between the content of information revealed and asset prices when the distribution of cash flow is unchanged following an information disclosure in theorem 4 (Resolution irrelevancy), which states that *"when changes in the resolution of uncertainty preserve the distribution of cash flows, they preserve current values"*.[44]

The opponents of the above theorems have been represented by Robert J. Shiller (2005) and characterized as *Irrational Exuberance*[45], which is a cornerstone in the theory of behavioural finance. He observes excessive exuberance and concludes that assets are not always priced correctly according to available information. The market can therefore not be efficient in its strongest form or semi-strong form due to the deviation from the asset prices fundamental value and the observed values. This is a direct violation of the martingale assumption that prices follow a random walk by Ross. In Subsection 2.2 we deal with the hypotheses about The Dispersion of Beliefs and the Effect of Noise Traders, which is another class of information hypotheses often related to behavioural finance.

The most important difference between the following information hypotheses is the separation of investors into informed and uninformed. MDH and SAIH do not separate these, while The Dispersion of Believes and The Effect of Noise Traders do. The terms *speculators*, *noise traders* and *irrational investors* are used indiscriminately in the following for uninformed investors, while the terms *arbitrageurs*, *hedgers*, *fundamental investors* are used indiscriminately for informed investors.

[44] Ross (1989), pp. 14.
[45] Shiller (2005). The expression was first used by Allan Greenspan at speech December 5, 1996. http://www.federalreserve.gov/boarddocs/speeches/1996/19961205.htm

2.2.3.1 The Mixture of Distribution Hypothesis (MDH)

The MDH seeks to explain the leptokurtotic distribution of price changes[46] in speculative assets by saying that daily price changes are sampled from a set of distributions with different variances.[47] The hypothesis of MDH is that daily price changes and trading volume are driven by the same information flow.[48]

The first theoretical work that sought to explain the volume-volatility relationship[49], which later became MDH, was made by Clark.[50] He found that when new information flows into the market, prices as well as traders' price expectations will change. If information is perceived differently across the market, prices will take longer time to adjust to the new information, entailing high trading volume as well as price volatility. The same will occur if the new information reaches different market participants at different paces. On the other hand, if information is perceived similarly across the market and at similar times, the price change might be large, however, the volume will be low, as the market will agree on the "correct" price level and the time to adjust market prices will be short. From this relation between trading volume and time to adjustment, Clark describes trading volume as an operational time instrument, an "imperfect clock", which measures the speed of evolution of the price change process[51].

The MDH theory has a number of different forms, e.g. one developed by Epps & Epps[52], who finds that the variance of the price change on a single transaction is conditional on the volume of that transaction. Another form of the model says that the daily price change is the sum of a number of independent intra-day price changes. This number of intra-day price changes is interpreted as the number of intra-day information arrivals, which makes the conditional variance of price changes an increasing function of the "information-rate".

The findings that both volume and price changes are driven by the information flow results in correlation between trading volume and price change, which is the key feature of the MDH. As

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[46] Fama (1965), pp. 34 – 105.
[47] Karpoff (1987), pp. 109 – 126.
[48] Luu & Martens (2002), pp. 1 – 32.
[49] Chen & Daigler (2008), pp. 963 – 992.
[50] Clark (1973), pp. 135 – 155.
[51] Clark (1973), pp. 135 – 155.
[52] Epps & Epps (1976), pp. 305 – 325.

variance in the information flow increases, so does the correlation between trading volume and volatility. Reversely, the volume-volatility correlation can be used to measure the rate and importance of the information flow.[53]

The concept of the MDH; that volatility and volume of speculative assets are driven by the same information flow is of high importance for this paper, both for constructing the empirical model and for discussing the empirical results.

2.2.3.2 The Sequential Arrival of Information Hypothesis (SAIH)

Like MDH the SAIH is based on the notion of a positive correlation between trading volume and price volatility. However, MDH focuses on contemporaneous changes in volume and volatility from current information flow, while SAIH deals with lagged information flows, volume and volatility. More specifically does the SIAH centre on information becoming known to different traders at different times.[54]

The hypothesis was first presented by Copeland.[55] He found that with sequential arrival of information, the information-adjusted new equilibrium price would be the same as in the case of simultaneous arrival of information. However the path to the equilibrium price will be different, as price will keep adjusting until all traders have adopted the new information in their demand function and acted accordingly. Copeland's sequential arrival of information model finds that trading volume is greatest when traders have unanimous opinions about the new information and smallest when traders disagree. This is in conflict with Clark's "imperfect clock" theory, which relates volume and price adjustment time, and was later criticised by Karpoff.[56] Nevertheless, the correlation between trading volume and volatility remains positive in SAIH; as it does in MDH. Furthermore, Copeland finds that trading volume and the path from the initial to the final equilibrium is a function of the total number of traders, the number of shares outstanding, the strength of the new information and the number of optimist out of the total number of traders.[57]

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[53] Chen & Daigler (2008), pp. 963 – 992.
[54] Chen & Daigler (2008), p. 968
[55] Copeland (1976), pp. 1.149 – 1.168.
[56] Karpoff (1987), pp. 109 – 126.
[57] Copeland (1976), p. 1.167

The fundamental premise of SAIH, that some traders receive information before others and thus market prices only reflect some information, or rather only reflect some traders reaction to the information, is similar to some of the concepts from the efficient market hypothesis[58] and the discussion of private vs. public information.[59]

2.2.3.3 The Dispersion of Believes hypothesis.

The Dispersion of Beliefs hypothesis[60] divide in contrast to the MDH and SAIH investors into informed traders with homogeneous believes and uninformed traders with heterogeneous believes, and explain the excess volatility from the dispersion in believes of future value of the uninformed traders.[61] Thus, excess volatility is a consequence of the way speculators interprets available information. Two assumptions are required for this hypothesis to hold. 1) Speculators and rational investors have different purposes for engaging in derivatives trading. Rational investors trade in derivatives to hedge future risk, while speculators are attracted by the low transaction cost and the possibility to earn a higher return on their investments. 2) The trade of speculators has to be significant relative to hedgers to affect the pricing process. An appropriate measure for this is the market depth, which has been defined as the order flow required to move prices by one unit.[62] Another possible explanation of the effect of traders' dispersion of expectations on volatility is described as a liquidity demand shock in the derivative markets. In this setting speculators' average demand for derivatives due to different interpretation of information causes a demand liquidity shock, which confuse the variation in asset prices following the announcement of new information, and creates excess volatility. An over responsiveness to demand liquidity shocks can therefore be identified with respect to the available information and the market participants interpretation of this information. In contrast, information resolved by noise trading may not be correct and uncertainty in the market may not be reduced. This is an ambiguity of The Dispersion of Believes Hypothesis, which makes it difficult to conclude anything about the theoretical effect of the hypothesis on the volatility.

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[58] Fama (1965), pp. 34 – 105.
[59] French & Roll (1986), pp. 5 – 26.
[60] Shalen (1993) & Harris & Raviv (1993) develop respectively this idea in relation to the future markets and in general.
[61] Pati (2008) draw an analogous comparison with speculative traders (uninformed) and fundamental traders (informed).
[62] Kyle (1985)

Empirical evidence suggests however a positive relation between the dispersion of believes of speculators and volatility, which support the former theoretical explanation of the hypothesis.[63]

The effect on the volume of the dispersion of believes by speculators is more clear, and explained by the presence of arbitrage possibilities, which will create excess volume from increased trading by both speculators and hedgers.

In addition, the Dispersion of Believes tend to increase in times with high uncertainty due to the difficulty in interpreting future average values of the asset prices, which supports the extensive empirical evidence of volatility clustering in financial times series. Furthermore, our choice of model (see Section 3) gives us the possibility to test the Dispersion of Believes hypothesis due to our distinction between speculators and hedger, which is approximated by volume and open interest respectively.

2.2.3.4 The Effect of Noise Traders.

This is an extension of the Dispersion of Believes Hypothesis to investigate the feedback from different trading activities.[64] Noise traders (Speculators) are assumed to exist in accordance to the dispersion of believes hypothesis. They will create an accumulative volatility effect due to the informed traders' missing response to the uninformed traders behaviour because of their risk adverseness and their short investment horizon. This means that noise traders will create excess volatility that diverge from the assets fundamental value, and that arbitrageurs will not try to exploit this fact. This view supports the separation of the volatility into fundamental volatility and noise.[65] Speculators must therefore bear the additional self-created risk themselves – often referred to as *Noise Trader Risk*[66] - which also results in a higher earned return on investments than for rational investors. Again, also this hypothesis violates the *Efficient Market Hypothesis* and Ross' Theorems, and makes noise trading an attractive alternative for speculators. The arbitrageurs lack of exploiting asset price deviations from its fundamental value emanates from two basic attitudes toward risk by arbitrageurs: 1) Rational investors are generally risk adverse to fundamental risk, which they try cope with by diversifying their portfolios. Risk above the fundamental market level is perceived as bad portfolio management according to Modern

[63] Chen (2008), pp. 969 – 970.
[64] DeLong et Al. (1990A) and DeLong et Al. (1990B)
[65] Hwang & Satchell (2000), pp. 761 – 764.
[66] DeLong et Al. (1990A), pp.

Portfolio Theory.[67] The unobserved fundamental volatility is general to all market participants and fluctuate in the same directions for every derivatives created from the same underlying asset. 2) Adverseness of the risk that the beliefs of noise traders will not revert to the mean for a long time, and the arbitrageurs therefore are forced to incur losses. In this relation pessimistic or optimistic behaviour of noise traders have been observed to affect asset prices in respectively short and long positions by the speculators.[68] This volatility caused by noise trading is specific to each derivative and is affected by the trading behaviour of speculators.

The mean-reversion property of financial times series, which is found when asset prices respond to noise[69] supports the properties of the data used to investigate the Swedish OMXS30 index. In our model we do not test the hypothesis whether noise trader activity have significant effect on the market pricing or creates mispricing due to the lack of exploiting arbitrage possibilities by rational investors. This will go beyond the scope of the problem statement and require a separate model for this purpose.

2.3 Econometric theory

2.3.1 Previous research

Previous research of how derivatives trading affect the underlying price volatility can be grouped into two broad categories, 1) Stochastic Volatility Models (SVM) and the family of ARCH/GARCH models. The two approaches have different point of origins and will therefore be treated separately in the following

In the following we will emphasize the ARCH/GARCH research due to the fact that these models are the most widely used for measuring the conditional variance in financial time series, and only briefly touch upon previously research related to Stochastic Volatility Models.[70]

First we investigate the development of the ARCH processes and then include studies where the models have been applied to the topic of derivatives effect on spot price volatility. Furthermore, the research on the concept of volatility will also be reviewed due to its importance for the main subject of this thesis. The various topics within the literature are quantified in tables throughout

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67 Markowitz (1976)
68 Shiller (2005). chapter 8 and 9 of Irrational Exuberance deals with this issue.
69 DeLong et Al. (1990A)
70 Bera & Higgens (1993): pp. 304 – 308.

the following section to emphasize the previously findings from the effect of derivatives trading activities. Finally, we use the results found in this section in conjunction with the results from the investigation of the statistical properties in a subsequent section to select the econometric model.

2.3.2 The family of ARCH and GARCH models

The research in ARCH models is vast and extensive, which makes it almost impossible to provide a comprehensive review. Bera & Higgins (1993) provide an in-dept review of some of the more important developments within the field of Autoregressive models, while Bollerslev et al. (1992) notice several hundred papers that apply the ARCH methodology to various financial times series. In the following we will focus on major contribution to the econometric theory of ARCH processes and thus leave out some minor improvements and variations of the ARCH process. Engle (1982) introduces the Autoregressive Conditional Heteroscedasticity (ARCH) process for forecasting and determine conditional variance of times series as an extension to the more general AR(p) model. This model takes into account observed values of the variance for forecasting future conditional variance and was a quantum leap in the econometric literature. Prior to the arrival of the ARCH model forecasts was based on the assumption of a constant one-period forecast variance. The model was applied to parameterize conditional heteroscedasticity in a wage-price equation (inflation) for the U.K. and found to be significant and obtained more realistic forecast variances than previous models. The model takes account of many observed properties of financial times series, which has lead to several interpretations and variations of the model.

Bollerselv (1986) and Taylor (1986) extend the ARCH model to a Generalized process (GARCH) independently to a model where the conditional variance is a linear function of its own lags. The difference between the ARCH and the GARCH models is the property that the unconditional autocorrelation function of the squared error term decay more slowly than for the ARCH process. This is a desired feature and fits the nature of observed financial times series where persistence in variance often is observed. An asymmetric approach to the GARCH model was introduced by Nelson (1991) and Glosten et al. (1993) to allow for asymmetric responses to shocks, which makes the EGARCH (Exponentially GARCH) model and the GJR-GARCH model nonlinear models. Recently the GARCH family of models have developed into a wide variety of models with different features desired in specific situations with respect to the properties of the investigated times series. These models are investigated by Bali et al. (2006) who provide an overview of the existing models. They find that the TS-GARCH and the EGARCH are the models that perform best in both in-sample and out-of-sample estimation. Contrary to this, Ederington et al. (2010) finds that the GARCH, TGARCH and EGARCH tend to overestimate the standard deviation of stock returns for forecasting purposes (out-of-sample estimation), and finds furthermore that the Absolute Restricted Least Squares model is more accurate in forecasting future standard deviation of stock prices.

For forecasting purposes the Sabiruzzama et Al. (2010) tests the GARCH versus the Threshold GARCH model (TGARCH) and finds that the TGARCH performs superior to the standard GARCH model due to its ability to capture asymmetric information which generates leverage effects. Pilar & Marquez (2007) conduct a similar research and extend the investigation into Stochastic Volatility Models to find the most appropriate model for out-of-sample volatility forecasting on the Spanish market. Their findings suggest that the SETAR-GARCH model generates the most accurate forecasts of future volatility and that the standard GARCH performs worst in forecasting.

In general, previous research agree on the attractiveness of the GARCH class of conditional volatility models due to some distinctive features that typically corresponds to the properties of financial times series such as, 1) the ability to capture the persistence in the volatility over time by a predetermined memory – referred to as volatility clustering 2) the ability to integrate asymmetric responses to shocks – often referred to as the "leverage effect", 3) the property of mean reversion.

2.3.3 Research on derivatives effect on spot price volatility

The empirical research on derivatives' effect on the underlying spot price volatility show ambiguous results but has generally been dominated by results that derivatives trading do not increase the long-run volatility of spot prices.[71] In the following we group the existing research into two categories based on their ways to tests the hypothesis whether derivatives trading affect the spot price volatility. Cross-sectional studies are included in the section concerning before-and-after studies, while experimental studies are leaved out due to its irrelevance to the subject. Research with the highest relevance for the main subject of this thesis is times series studies.

[71] Sutcliffe (1993); pp. 323 – 324.

2.3.4 Comparison of the volatility before and after the introduction

This is by far the most tested hypothesis of the effect of derivatives trading on the underlying assets and has been conducted for several countries and spot markets where trading in derivatives exists. Antoniou and Holmes uses both an GARCH and an intergraded GARCH model to investigate the volatility effect of Stock Index Futures on a daily basis on the FTSE-100 index following its introduction in 1984. Their findings suggest that the volatility has increased following the introduction, but they also conclude that the nature of volatility remains unchanged and exhibit persistence in variance and volatility clustering. They also address the relationship between information and volatility and finds that futures' trading improves both the speed of information flowing to spot markets and the quality of information. This suggests the increase in volatility is related to improvement in information flow and not due to adverse destabilizing effect caused by speculators. Shembagaraman (2003) come to contrary results using daily data on the Indian NIFTY index and a GARCH(1,1) process, and conclude that the nature of volatility has changed compared to the pre-futures period and that the volatility has increased.

Boyer et Al. (2003) uses a market model to find the volatility before and after the introduction of Index Futures on the S&P500 index and finds no evidence for increased volatility after the introduction. Also Mallikarjunappa et al. (2008) finds no evidence of neither stabilizing effects nor destabilizing effect after the introduction of futures and options on the Indian NIFTY index by using a GARCH model. Clustering and persistence in volatility is found, which support the choice of the GARCH model. Previous research is also criticized of emphasizing the effect on volatility and not how the rate of information flow relates to spot price volatility.

Robbani et Al. (2004) finds increased volatility on component stocks in the Dow Jones Industrial Average (DJIA) Index brought by irrational investors after the introduction of index futures and options. They use a non-parametric approach and a GARCH model to test the volatility of the underlying stocks in the index and find that only 3 of 30 stocks exhibit a decrease in the volatility. The increased volatility in component stocks indicates that, even though a higher liquidity is found, the destabilizing effect brought by irrational investors outweighs the beneficial liquidity effect. In contrast to these findings Rahman (2001) finds no significant change on an index level on the DJIA index using a GARCH model.

Reyes (1996) investigates the French and Danish stock market using the Exponential GARCH model imposed with dummy variables to control for the effect before and after the introduction of index future trading. The volatility is found to decrease, while increased information flow is found to induce symmetry among traders and thereby not encourage speculative investors to destabilize the market. A similar approach have been taken by Bologna et Al. (2002) with data from the Italian market to test whether an observed reduction in volatility in the MIB30 index can be explained by the introduction of trading in index futures by using a GARCH model with dummy variables. They find that the decreased stock market volatility can be fully explained by the introduction of derivatives trading, which support the theories stating that future trading will improve the efficiency of the underlying spot markets. Pilar et Al. (2002) uses a similar approach on the Spanish IBEX-35 index following the introduction of index futures by a GJR-GARCH model (TS-GARCH) on daily observations and find same results; decreasing volatility and improved market efficiency.

On the individual stock level Calado et. Al . (2005) investigates the effect of derivatives trading using a daily GARCH(1,1) process, and finds that some stocks have experienced both significant decreases and increases in the volatility. This ambiguous result is also found on an index level by Floros et Al. (2006) where they investigate both the FTSE/ASE-20 index and the FTSE/ASE-mid-40 index. The introduction of derivatives trading is found to increase the volatility in the FTSE/ASE- mid 40 index by using various GARCH models while a decrease is found in the FTSE/ASE-20 index. Liu (2009) also finds a reduced volatility on component stocks of the S&P100 index after introduction of index options as a support of an improved information flow to spot markets.

Another approach taken by Hwang et Al. (2000) uses a Stochastic Volatility Model to determine the volatility before and after the introduction of European options on the FTSE100 index. They find no destabilizing effect from the introduction but finds persistence in volatility and high correlation between noise in the derivatives markets and noise in the underlying spot markets.

Also Sorescu (2000) investigates the effect of options listing on the S&P500 by using a two-regime switching mean model. He finds increased volatility after the introduction, but conclude that the increase best can be described from other external events affecting the volatility and returns of the spot markets.

Finally, the ambiguity about the empirical evidence whether the introduction of futures contracts affect the volatility of the underlying spot market can be highlighted by Altay-Salih et Al. (1998), who investigates 24 different indexes before and after the introduction of index futures. They find that 17 markets exhibit lower long run volatility. Both the short run volatility and the relation between volatility and information flow are not touched upon, which leaves space for further investigation into the subject.

The following two tables summarize the effect on the underlying spot volatility within before – and after studies of index futures/options and component futures/options respectively.

Table 2.1. Previous research of the effect from Index Futures listing on Volatility - Before/After studies

				The effect on Volatility		
Study (Author)	**Index**	**Period**	**Methodology**	**Up**	**Unchanged**	**Down**
Altay-Salih et Al. (1998)	24 indexes	1982 - 1996	GARCH / SVM	X (3/24)	X (4/24)	X (17/24)
Antonio et. Al. (1995)	FTSE-100	1980 - 1991	GARCH	X		
Baldauf et Al. (1991)	S&P500	1975 - 1989	ARCH			X
Bassembinder & Seguin (1992)	S&P500	1978 - 1989	Multivariate models	X		
Bhargava et Al. (2007)	DM/BP/JY	1982 - 2000	GARCH	X		
Bologna & Cavallo (2002)	Italian IDEM	1990 - 1998	GARCH			X
Boyer & Popiela (2003)	S&P500	1977 - 1992	A Market model		X	
Butterworth (2000)	FTSE Min 250	1992 - 1995	GARCH	X		
Calado et Al. (2005)	BVLP (Portugal)	1997 - 2001	Multivariate models		X	
Debasish (2008)	NSE Nifty	2000 - 2007	FPE/Jump Volatility		X	
Floros & Vougas (2006)	FTSE/ASE Mid 40	1997 - 2001	EGARCH / TGARCH/SVM			X
Gulen & Mayhew (2005)	25 Market indexes	1973 - 1997	GARCH	X	X	X
Kim, Kim & Kim (2004)	KOSPI 200	1996 - 2002	EGARCH	X		
Mallikarjunappa & Afsal (2008)	S&P CNX Nifty Index	2000 - 2007	GARCH		X	
Pilar & Rafael (2002)	IBEX-35 (Spain)	1990 - 1994	GJR-GARCH			X
Reyes (1996)	CAC-40	1987 - 1993	EGARCH	X		(x)
Shenbagaraman (2003)	S&P CNX Nifty Index	1995 - 2002	GARCH / Multivariate models		X	
Rahman (2001)	Dow Jones IA	1997 - 1998	GARCH		X	
Dawson & Staikouras (2009)	S&P500	2000 - 2008	GARCH	X		
Robbani & Bhuyan (2004)	DJIA	1996 - 1998	GARCH	X		

Table 2.2. Previous research of the effect from Option listion on Volatility - Before/After studies

				The effect on Volatility		
Study (Author)	**Index**	**Period**	**Methodology**	**Up**	**Unchanged**	**Down**
Calado et Al. (2005)	BVLP (Portugal)	1997 - 2001	Multivariate models		X	
Conrad (1989)	CBOE options	1973 - 1980	A Market model			X
Hwang & Satchell (2000)	FTSE-100	1984 - 1996	SVM			X
Kim, Kim & Kim (2004)	KOSPI 200	1996 - 2002	EGARCH	X		
Kumar et Al. (1998)	S&P500	1983 - 1989	VAR			X
Liu (2007)	S&P100	1983 - 1989	Multivariate models/VAR			X
Mallikarjunappa & Afsal (2008)	S&P CNX Nifty Index	2000 - 2007	GARCH		X	
Pilar & Rafael (2002)	IBEX-35 (Spain)	1990 - 1994	GJR-GARCH			X
Reyes (1996)	CAC-40	1987 - 1993	EGARCH	X		(x)
Shenbagaraman (2003)	S&P CNX Nifty Index	1995 - 2002	GARCH / Multivariate models		X	
Sorescu (1999)	US Stock options	1973 - 1995	Two regime swithing mean model			
Rahman (2001)	DJIA	1997 - 1998	GARCH		X	
Robbani & Bhuyan (2004)	DJIA	1996 - 1998	GARCH	X		

A major concern about the above event studies is the use of only one estimation to conclude upon the volatility effect of derivatives and the methodology is therefore often open to question.[72] Macroeconomic variables or other uncontrolled variables may contaminate the volatility observations and make the conclusion illusive. This issue is addressed by Schwert (1989) who investigates the relation between spot market volatility and some macroeconomic variables using an ARCH process. He finds that high persistence in volatility and asymmetric responses shocks, especially during recessions (leverage effects), and the trading volume as the leading indicator for explaining the spot market volatility.

2.3.5 Times-series studies

These studies are trying to explain the volatility of the underlying asset from a variety of economic variables. In the following we focus on research concerning the trading activity of derivatives.

Kim et Al. (2004) investigates the relationship between the trading activities on the highly liquid South Korean KOSPI 200 index by using open-interests, volume and daily closing prices. They use an EGARCH model in a simultaneous equation model and a three-stage least squares method for estimating the parameters to calculate the intra-day volatility. Their findings suggest that unexpected trading volume in futures increases the spot volatility, while expected trading activity in futures stabilizes the spot markets. They interpret this finding, as speculative investors are irrational and increase the spot volatility while hedging activities tend to stabilize the stock markets. Park et Al. (1999) finds similar results for equity options on the 45 most traded options contracts listed on the Chicago Board of Options Exchange by using an asymmetric GARCH model and an ARIMA model. These findings support the hypothesis that trading in equity options does not systematically destabilize the underlying spot markets.

Kiymaz et Al. (2009) apply the GARCH and TGARCH model imposed with volume variables on the emerging Turkish market. The GARCH model is found to be an appropriate model for explaining conditional variance. A negative relation between trading volume and volatility is found, which suggest that more information is reviled when the trading volume increases and the market transparency is improved. In addition, no sign of leverage effects are found in the spot

[72] Sucliffe (1993); 324 – 327.

markets. Debasish (2008) uses the FPF/multivariate Granger causality modeling technique to examine whether activities in the futures markets and other relevant factors have caused Granger-caused jump volatility on the Indian market. They find no supporting evidence of increased volatility, but conclude that asset returns exhibit persistence in volatility.

Bassembinder & Seguin (1992) divide trading activities in futures into expected and unexpected trading (shocks) and examine the S&P500 in the period 1978 to 1989. They use daily data for volume and open-interests on futures and calculate the conditional volatility from a GARCH process. They find a positive relationship between unexpected futures trading and spot market volatility suggesting that speculators destabilize the market and no relationship between the futures lifecycle. The findings support the theories predicting enhanced liquidity and dept of the spot markets from active futures trading. Bassembinder & Seguin (1993) uses the same approach on eight different financial markets and come to the same conclusion. Furthermore, in this research they also find a greater relation between the volume in the spot markets and the volatility than for the futures markets. This makes sense from a theoretical supply-demand point of view. Also Chatrath et Al. (2003) uses this approach on the S&P500 index futures and find a positive relationship between increases in Volume and stock market volatility. Their findings are not conclusive whether the increased volatility is due to an increase in the information or destabilizing effects from speculators. Sutcliffe (2001) uses both an GARCH model and a Stochastic Volatility Model to estimate the effects from trading activities on the underlying spot markets. He use daily data from the FTSE 100 index and find that the best-fit model is the SVM. The GARCH model is found to be inappropriate and leads to different conclusions than the SVM. Furthermore, the Volume parameter of the GARCH model if found often to be misinterpreted.

The relationship between futures trading and the volatility of futures prices has been investigated by Pati (2008) who uses an ARMA-GJR-GARCH model to any evidence for increased volatility. Trading volume is divided into expected and unexpected and a positive relation between unexpected volume and volatility of futures prises is found. Open interests is likewise divided into expected and unexpected volatility and a negative relation between expected Open interests and volatility is found. This supports the information hypotheses (see Subsection 2.2), which also are reviewed. Both Chen et Al. (2008) and Yen & Chen (2010) uses a Vector Autoregressive Model and a standard GARCH model for three Taiwan stock index futures markets to test the information hypotheses. They find that the information flow most accurately can be described as a combination of the four information hypotheses and that a positive relation is found between unexpected volume shocks and volatility.

The below table summarize our findings from the previous literature on the relation between trading activities in derivatives and the underlying spot volatility.

Table 2.3. Previous research of the relation between trading activity and volume

				The effect on Volatility		
Study (Author)	**Index**	**Period**	**Methodology**	**Up**	**Unchanged**	**Down**
Kiymaz & Girard (2009)	Istanbul N30	1988 - 2005	TGARCH	X		
Conrad (1989)	CBOE options	1973 - 1980	A Market model			X
Hwang & Satchell (2000)	FTSE-100	1984 - 1996	SVM			X
Kim, Kim & Kim (2004)	KOSPI 200	1996 - 2002	EGARCH	X		
Kumar et Al. (1998)	S&P500	1983 - 1989	VAR			X
Liu (2007)	S&P100	1983 - 1989	Multivariate models/VAR			X
Mallikarjunappa & Afsal (2008)	S&P CNX Nifty Index	2000 - 2007	GARCH		X	
Pilar & Rafael (2002)	IBEX-35 (Spain)	1990 - 1994	GJR-GARCH			X
Reyes (1996)	CAC-40	1987 - 1993	EGARCH	X		(x)
Shenbagaraman (2003)	S&P CNX Nifty Index	1995 - 2002	GARCH / Multivariate models		X	
Sorescu (1999)	US Stock options	1973 - 1995	Two regime swithing mean model			
Pati 2008	Nifty	2001 - 2008	ARMA-GARCH	X		(x)
Sutcliffe et Al. (2001)	FTSE-100	1988 - 1995	SVM/GARCH			X
Yen et. Al. (2010)	TAIEX	1998 - 2007	VAR/ARMA-GARCH/EGARCH	X		
Park & Switzer	S&P500	1990 - 1991	GARCH	X		

From the investigation of the previous literature we can conclude that the effect of trading activities in derivatives is ambiguous. Many investigations have been conducted as before and after studies where the different researchers have found different results in the same investigated periods and for the same indexes. This suggests that their findings results are highly depended upon investigation methodology and the econometric model used. The same results are found for the previous literature about the relation between trading activities in derivatives and the volatility. We also find from previous literature that the most used model measuring the conditional variance in the recognized GARCH-type of models in several variations. To replicate the stylized facts of financial time series we find the EGARCH and GJR-GARCH[73] models to be the most prominent.

[73] The Threshold GARCH (TGARCH) is a variation of the GJR-GARCH, where the conditional standard deviation is measured and not the conditional variance as in the GJR-GARCH.

2.4 Part conclusion on the theoretical framework

From the financial theory we identified three types of traders; *Arbitrageurs, Speculators* and *Hedgers*. The effect from arbitrageurs is found small and insignificant do to the increasing efficiency of financial markets, while trading activities of speculators and hedgers are more effective on the derivatives market. Hedgers mainly use derivatives to manage risk they are exposed to from long positions in the market, which is the one of the fundamental purposes of derivatives markets. In contrast, speculators take positions in derivatives to earn a higher return on investment by not holding the underlying asset. Thus their investments are leveraged, which in theory has a destabilising effect on the underlying market.

In the preceding section we also established a link between the information rate, price volatility, volume and their interrelations though a theoretical framework based on how the information flow affect the price volatility (Ross' theorems and behavioural finance). Several information hypotheses was discussed, which can be related to both derivatives markets and sport markets. The investigated information hypothesis can in general be divided into two theoretical approaches based their assumptions regarding uninformed traders. Both the MDH and the SAIH do not make this distinction and takes no irrational factors into account, while both the Dispersion of Believes and the Effect of Noise Traders does.

From the MDH a positive relation between the information flows and both volume and volatility was found. Daily price changes and trading volume are thus governed by the same information flow. A leptokurtic distributional property was recognized in asset returns, which fits our choice of model and makes it possible for us to relate our empirical findings to the hypothesis.

The SAIH also suggest a positive relation between volatility and volume, but deals instead with lagged information flows. The equilibrium price is the same as with the MDH, but the information arrival process happens through a sequential process rather than a simultaneous process. Some investors are therefore supplied with essential information before others, which gives them an advantage in the market. Even though the SAIH recognizes this fact it does not explain how agents with superior information can affect equilibrium prices by exploiting this information.

The Dispersion of Believes Hypothesis has its origin in behavioural finance and separates investors into informed (hedgers) and uninformed (speculators). The speculators are assumed to take up a significant size and the dispersion of their expectations will therefore crate excess volatility and volume. Thus, the greater the dispersion of believes the grater the reaction to arrival of new information to the market. This hypothesis can be related to our empirical results due to our choice of model, where we divide trading activity into hedgers and speculators. In addition, the hypothesis supports the extensive evidence of volatility clustering in financial time series.

The Effect of Noise Traders was also considered. In this setting hedgers are passive to the behaviour of speculators, who creates excess volatility and thereby earn a higher rate of return by bearing their own self-created risk. The relationship between information flow, volatility and volume is therefore found to be positive.

In sum, all informational hypotheses suggest a positive relation between information flow and volume, while the evidence on volatility are more uncertain, but still recognized in most of the hypotheses.

Finally, from research of modelling conditional volatility we found that two models are more dominant than others; the Stochastic Volatility Model (SVM) and the Generalised Autoregressive Conditional Heteroscedasticity model (GARCH). Both models were found appropriate in dealing with in-sample modelling of stochastic processes. We selected a GARCH-type of model due to its closed form solution and the popularity in other researches.

3 Empirical model selection

The purpose of this section is to find which type of GARCH model that best capture the stylized facts of financial time series also investigated in this section. This is done by investigate the data from an econometric perspective and present the econometric foundation for this thesis.

3.1 Statistical properties of the data

In this section we examine the statistical properties of the financial time series data used in the empirical investigation of this thesis. The statistical properties of the data (sometimes referred to as the stylized facts) will in conjunction with the investigation of the previous literature be the basis for our choice of model, as the preferred model is the one that best captures the features of the data. The stylized facts of the data that we will investigate are volatility clustering, leptokurtosis and stationarity, which are the stylized fact we find most relevant in relation to financial time series on basis of previous research.[74]

3.1.1 Volatility clustering

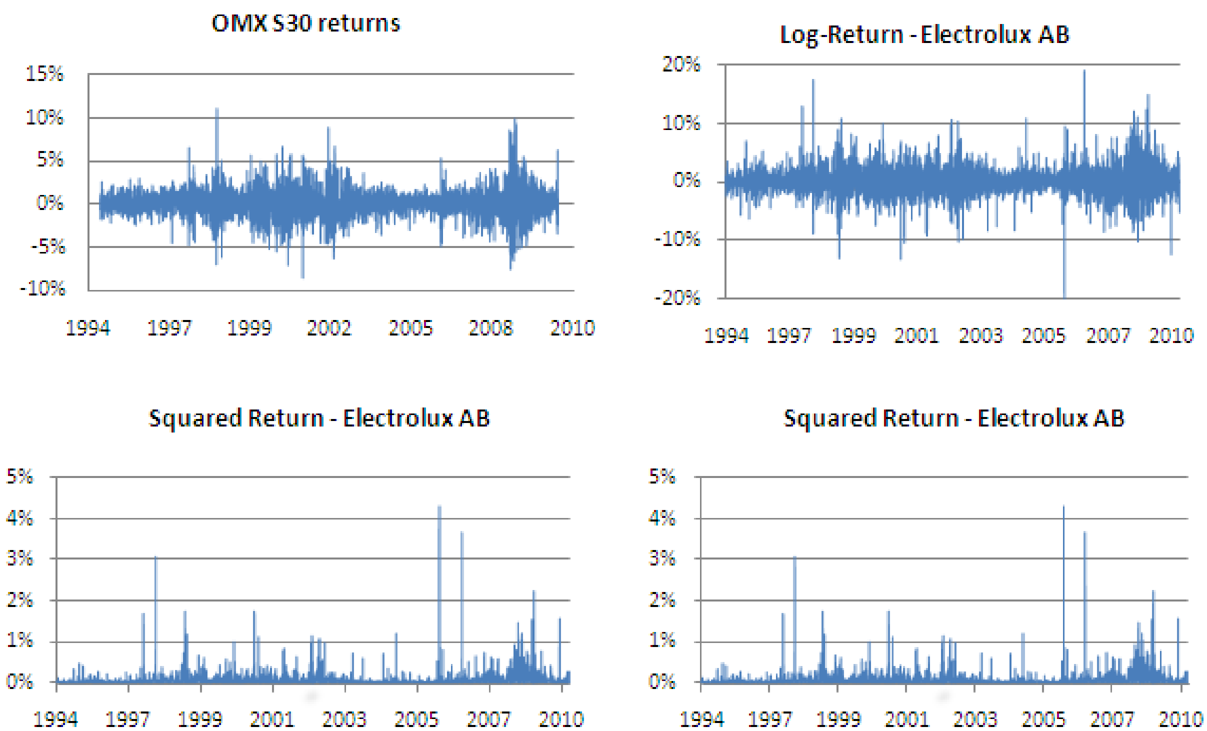
The graphs in Figure 3.1. show log returns,$r_t = ln\left(\frac{P_t}{P_{t-1}}\right)$ and squared returns, r_t^2 on a daily basis for the OMX S30 Index and Electrolux for the period 1992 (1994 for Electrolux) to May 2010 (similar plots for the rest of the investigated companies can be found in appendix 2, which we have conducted to make sure all companies exhibit similar patterns). The graphs of log returns show some level of persistence, though it is not very obvious. However, the graphs of squared returns indicate persistence, which is a sign of volatility clustering. Volatility clustering implies that low values of volatility are followed by low values of volatility and high values of volatility are followed by high values of volatility.[75]

Volatility clustering is often present in financial time data, e.g. asset prices, which reflect that prices are a result of trading between buyers and sellers, various sources of information and other exogenous economic shocks that may have an impact on the time series pattern of asset prices. Given that information lead to various interpretations, and exogenous economic shocks, such as bust of economic bubbles or oil crises often will last for a longer period, we often see that large fluctuations in financial time series tend to appear in clusters.[76] This phenomenon also supports

[74] Cont (2000); p. 224
[75] Andersen et al (2009) p. 114
[76] Franses (1998) p. 155

the information hypothesis about the dispersion of believes, where differences in the interpretation of information leads to volatility clustering.

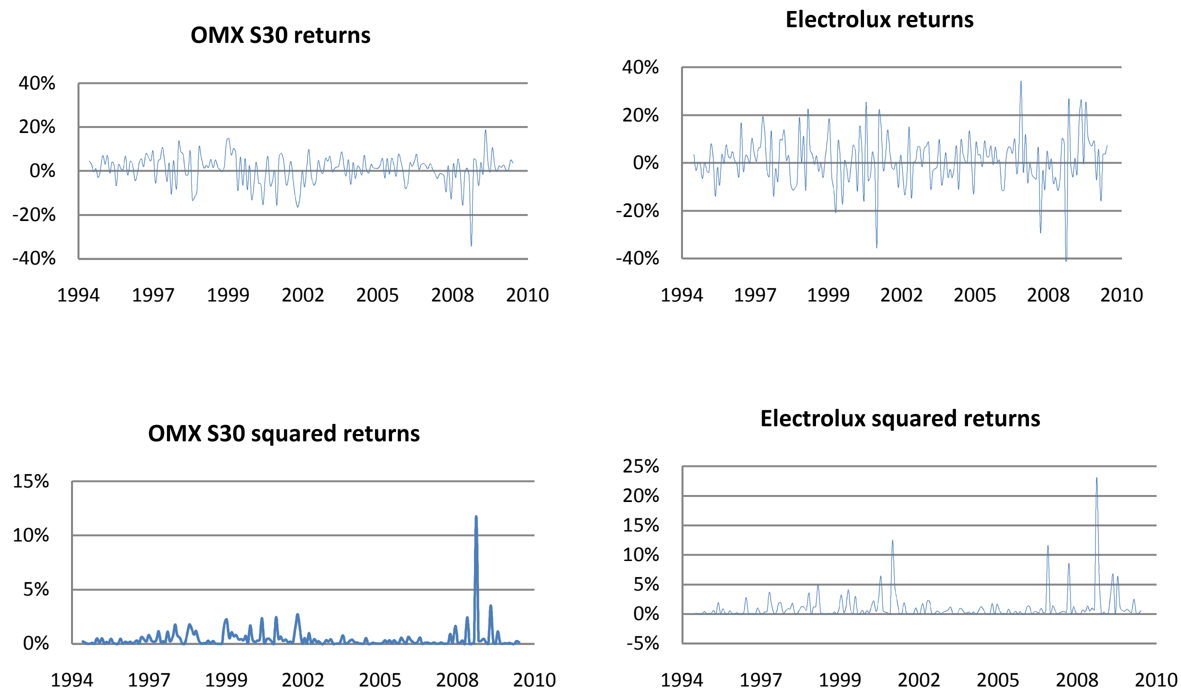
Figure 3.1 Daily returns and squared returns for OMXS30 Index and Electrolux



In Figure 3.2. we have created graphs that are similar to the ones in Figure 3.1.: log returns, r_t and squared returns, r_t^2 – with the difference that the graphs in Figure 3.2. are based on monthly returns instead of daily returns.[77] The monthly return data display less volatility clustering – if anything at all – than the data for daily returns. Thus the factors that causes volatility clustering, such as exogenous shocks to the economy and the flow and interpretation of information will not generate large variances in the volatility over longer periods of time, though they have the ability to create persistence in the return levels for shorter periods, such as days or weeks.

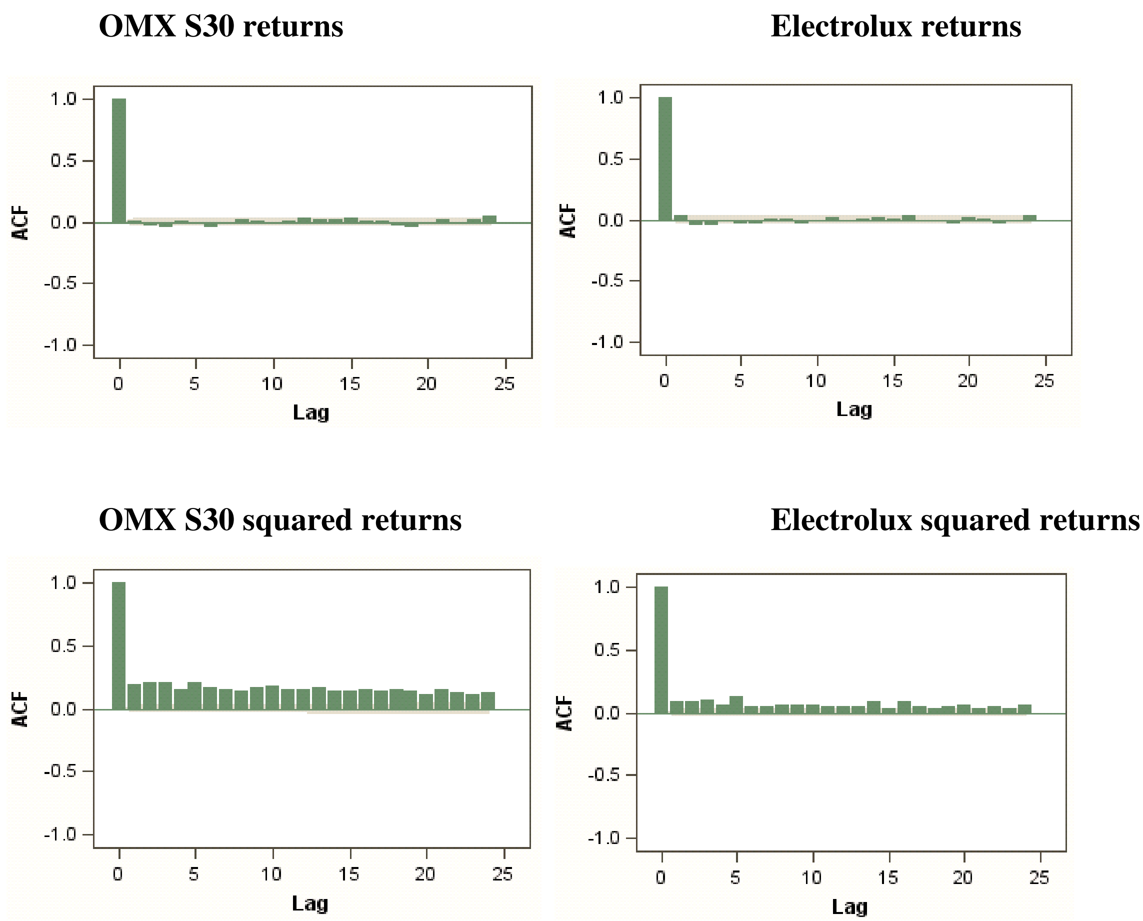
[77] Monthly return are calculated as the return over intervals of 21 trading days (a year consists of 252 trading days on average, which comes out to 21 monthly trading days on average).

Figure 3.2 Monthly returns and squared returns for OMX S30 Index and Electrolux



The correlograms in Figure 3.3. show the sample autocorrelation for r_t and r_t^2 at various lags for OMX S30 and Electrolux. The correlograms for log return give an indication of no significant autocorrelation. Oppositely, we see that the correlograms for squared return show significant positive correlation, which support our observation in the graph of squared returns, and is an indication of volatility clustering.

Figure 3.3 ACF correlograms of sample autocorrelation for daily returns and squared returns



From our graphical investigation we find clear signs of volatility clustering in squared returns for both the Index OMX S30 and the Electrolux stock. Volatility clustering indicates (at least) two things. Firstly, the variance of returns varies over time, which is known as heteroscedasticity or unequal variance. Secondly, the unequal variance has an autocorrelated structure. These features indicate that the time series of returns contains so-called ARCH (autoreregressive conditional heteroscedasticity) processes. In section 3.4.1. we give a more thoroughly introduction to ARCH processes/models but the key feature is that the variance of the error term, $var(\varepsilon_t)$, is conditioned on the (squared) previous error terms, ε_{t-1}^2, thus giving an impression of autocorrelation.[78]

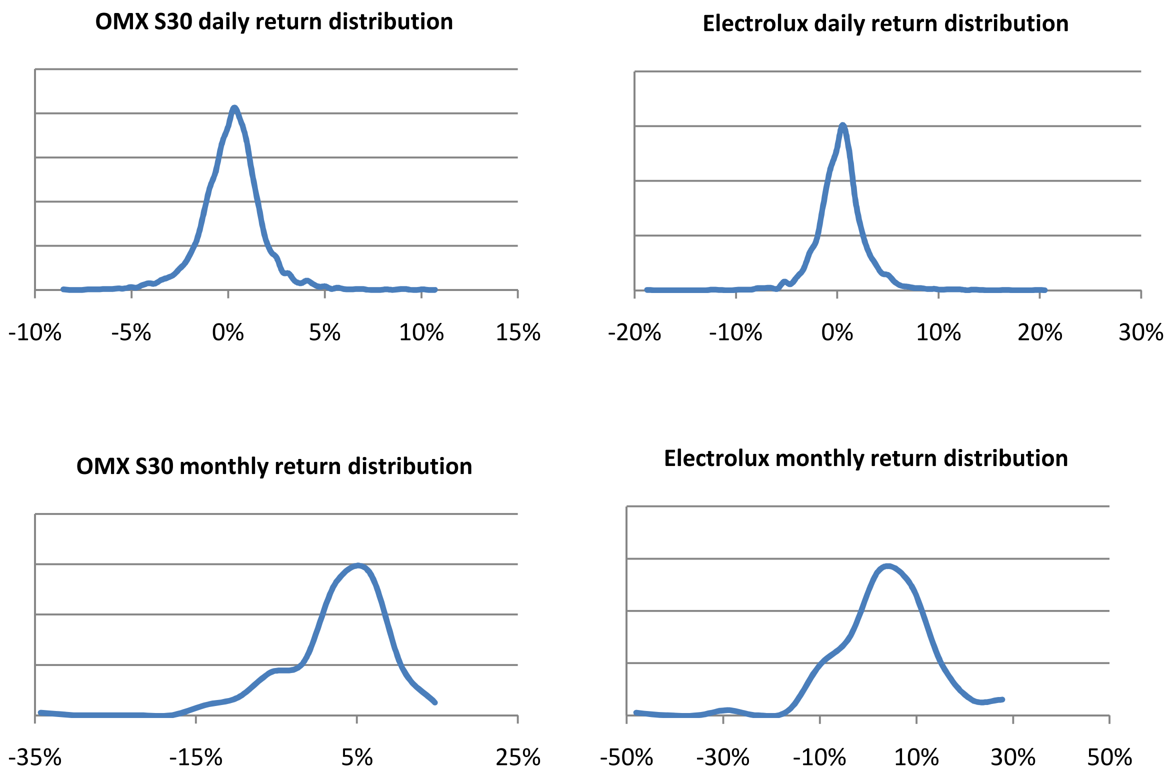
[78] Gujarati, Damodar N. (2003) p. 859

3.1.2 Leptokurtosis

A key property of many financial data series is that they are not normally distributed but instead exhibit skewness and excess kurtosis. In Figure 3.4. below we show the distribution of the daily returns for OMX S30 and Electrolux respectively.

The rather pointy shape of the curve indicate a leptokurtic distribution, which imply a more slim and fat tailed distribution curve compared to a normal distribution. The fatter tails indicate relatively more weight in the tails and hence more 'extreme' and less moderate observations compared to a normal bell shaped distribution. From a graphical inspection of the daily return it is difficult to determine if the distribution is skewed to either right or left, as it looks rather symmetrical around a positive mean. In contrast, the distributions for monthly return in Figure 3.4. for both OMX S30 and Electrolux does not appear normal distributed either. They both have rather fat tails, thus indicating excess kurtosis as well as left skewness or lack of symmetry around the mean. As a note we observe that the mean is higher for monthly return than for daily return. This is of course a natural consequence of the fact that each observation is return measured over one month compared to the return of a single day.

Figure 3.4 Distribution of daily returns for OMX S30 and Electrolux



In table 3.1. we have displayed the summary statistics for daily return for OMX S30 and Electrolux, as well as the summary statistics for monthly return for reference. The Jarque Bera test for normality is a joint test of the skewness and kurtosis of a distribution. A normal distributed variable has skewness = 0 and kurtosis = 3, thus the Jarque Bera test the joint hypothesis that skewness = 0 and kurtosis = 3. Under this hypothesis, that the residuals are normally distributed, the Jarque Bera statistic follows the chi-square distribution with two degrees of freedom. Not to reject the the normality hypothesis on a 1%-confidence level the Jarque Bera statistic should be no more than 9.21. Thus the JB statistics of 2034 and 7220 for the daily returns of OMX S30 and Electrolux clearly rejects the normality hypothesis[79].

Furthermore, with normal kurtosis = 3, the kurtosis statistics of 6.53 and 9.59 clearly indicates excess kurtosis for both OMX S30 and Electrolux. This confirms our supposition from the graphical inspection, namely that the time series exhibit leptokurtosis.

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[79] Gujarati, Damodar N. (2003) p. 148-149 and p. 968 for chi-square distribution table

Table 3.1. Summary statistics for daily and monthly stock return

Asset	Obser.	Mean	Max	Min	Std. Dev	Skew	Kurt	Jarque Bera
Daily returns								
OMX S30	3893	0,0339%	11,02%	-8,53%	1,59%	0,1173	6,5335	2034
Electrolux	3893	0,0744%	21,15%	-18,78%	2,44%	0,5205	9,5899	7220
Monthly returns								
OMX S30	186	0,7397%	18,78%	-34,30%	6,58%	-1,1637	7,1042	173
Electrolux	193	0,8671%	34,12%	-48,05%	10,30%	-0,4297	6,2895	93

3.1.3 Stationarity

A central property when investigating stochastic time series is stationarity. "*A stochastic process is said to be stationary if its mean and variance are constant over time and the value of the covariance between the two time periods depends only on the distance or gap or lag between the two time periods and not the actual time at which the covariance is computed*".[80] This means that for a time series to be stationary its mean, variance and autocovariance (for various lags) must be the same at all times. Thus, a non-stationary time series will have a time-varying mean, time-varying variance or both.

A constant mean and variance implies that the time series will have fluctuations (measured by the variance) with broadly constant amplitude around the mean. Hence, the time series has the tendency to return to its mean, called mean reversion. The speed of the time series' reversion to the mean is determined by the degree of autocovariance in the time series. If there is a high degree of autocovariance and/or autocovariance in lags far from the current time period, there will be persistence in the time series shocks, and the variable will take longer time to return to its long term mean. Oppositely, if there is a low level of autocovariance, the shocks will not be transmitted to the following observations and the time series will return to its mean.

The consequence of a time series being non-stationary is that it has little practical value for forecasting, as any properties obtained by analysis will only apply for that specific analysis period. Oppositely, if a time series is stationary, one can generalise findings from a representative research period and use it to forecast future behaviour of the time series.

[80] Gujarati, Damodar N. (2003) p. 797

Looking at Figure 3.1. of daily returns for OMX S30 and Electrolux, we observe that daily returns fluctuate around a somewhat constant mean for the entire period. In case daily returns have had an either upward or downward trending mean, it would have implied that daily returns would in general have gone up or down over the period under analysis. Regarding the variance of the OMX S30 and Electrolux it does not appear constant as there are periods that indicate higher volatility than others. Even if we removed the extreme observations (or outliers) that appear as spikes in the graph, there would still be a tendency of a time-varying variance. This property becomes more distinct if we square the daily returns, as we did in a previous section regarding volatility clustering (Figure 3.1.)

To test whether or not our time series is stationary, we employ the augmented Dickey-Fuller test, which test for the presence of a unit root in our data, that is the data is non-stationary. The Dickey-Fuller test tests if $\rho = 1$ in the equation: $Y_t = \rho Y_{t-1} + u_t$, which would imply that today's value is equal to yesterdays value plus a random shock. For our examples OMXS30 and Electrolux, we reject the unit root hypothesis of non-stationarity and conclude that both time series are stationary. The results of the augmented Dickey-Fuller test are displayed in Appendix 3.

A property of non-stationary processes is that their first differences, $\Delta Y_t = Y_t - Y_{t-1}$, are stationary. (This is the case if they integrated of the order 1. If the process contains x unit roots, it has to be integrated x times to become stationary). In the present analysis the time series are in fact first differenced data in percentage terms, as they are daily returns and hence the percentage difference in index/stock prices from $t-1$ to t. Going one integration step backwards, we investigate the raw data series, the index values and stock prices. From the index/stock price graph, the correlograms and augmented Dickey Fuller test results displayed in Appendix 3, we conclude that the raw data series are non-stationary.

By examining the stylised facts of the data we find that the time series exhibit the properties that are traditionally associated with ARCH/GARCH type models, such as volatility clustering, leptokurtosis and stationarity (containing mean reversion). Together with our review of the literature in this area, this supports our choice of a GARCH-type model for our empirical investigation, as it is one of the best models to capture the properties of our data, and in general in financial time series. In the next section we will investigate the elements and properties of the ARMA-GARCH model in-depth.

3.2 Choice of model

The econometric literature has proposed a range of models to best capture the stylised facts of financial time series, e.g. asset returns, as we described in the literature review. Based on the review we settled on an ARMA-GJR-GARCH model as the volatility model that would best meet the requirements of capturing the statistical properties of the return data, analysed in the previous section. In this section we will explore the different elements included in the ARMA-GJR-GARCH model. First, we investigate the autoregressive moving average (ARMA) processes in the conditional mean specification part of the model. This part of the GARCH framework is often referred to as the first moment of financial time series. Hereafter, we describe the model's generalised autoregressive conditional heteroscedasticity (GARCH) processes in the conditional variance specification part, which is often referred to as the second moment of financial time series. Moreover, in line with the GJR-GARCH framework of conditional variance, we add a dummy variable in order to capture the asymmetric leverage effect, that is, the circumstance that negative shocks tend to have a larger impact on the volatility than positive shocks. Last in this section we add measures of derivatives trading activity, consisting of volume and open interest. These final measures of derivatives trading activity change the general ARMA GJR-GARCH for conditional volatility into a model suitable for testing the hypotheses of this thesis, namely testing the effect of derivatives trading on the volatility of the underlying asset. With the empirical model defined in this section, it naturally leads up to the next part of the thesis, which is model specification and parameter estimation based on our time series data of daily returns.

3.3 ARMA modelling

Compared with traditional use of the GARCH model the ARMA processes of ARMA-GARCH modelling of daily returns series removes the predictability associated with lagged returns by adding a sufficient number of autoregressive (AR) and moving average (MA) terms in the mean equation.[81] As noted, the ARMA term consists of two types of processes, an autoregressive (AR) process and a moving average (MA) process, which we will explain in the following.

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[81] Pati, Pratap Chandra (2008) pp. 34-35

The general AR process, described as deviation from the mean, looks as follows

$$(Y_t - \delta) = \alpha_t(Y_{t-1} - \delta) + \varepsilon_t$$

or

$$y_t = \alpha_1 y_{t-1} + \varepsilon_t$$

, where δ is the mean of Y, $y_t = (Y_t - \delta)$ and ε_t is an uncorrelated random error term with zero mean and constant variance, $\varepsilon_t \sim (0, \sigma^2)$.

We say that y_t follows a first-order autocorrelation, or AR(1) process. In other words y_t can be expressed as some proportion (α_1) of its value in the last period (y_{t-1}) plus a random shock or disturbance at time t, ε_t. When the conditional mean is explained by its value at several lags

$$y_t = \sum_{j=1}^{p} \alpha_p y_{t-p} + \varepsilon_t$$

, it follows a *p*th-order autoregressive, or AR(p), process.

In the preceding model there are no other regressors than lagged values of the regressand itself and hence the *”data speak for themselves”*.[82] Notice also that in the special case were a AR(1) process has the estimate $\alpha_1 = 1$, the model is a random walk.

The MA process is another mechanism that may have generated *y*. The MA process represent lagged error terms, which in its simplest form, a so-called first-order moving average, MA(1), process looks as follows

$$y_t = \mu + \beta_0 \varepsilon_t + \beta_1 \varepsilon_{t-1}$$

, where μ is a constant and ε_t is a white noise error term. Similar to the extension of the AR process, where we included additional lagged values of *y* as regressors, we extend the MA process to include *q* number of lagged error terms as regressors

[82] Gujarati, Damodar N. (2003) pp. 838-839

$$y_t = \mu + \sum_{j=1}^{q} \beta_q \varepsilon_{t-q}$$

As we see, a moving average process is simply a linear combination of white noise error terms.[83]

It is often the case that y is generated by both AR and MA processes, thus they are combined to an ARMA(p,q) process, which consists of p autoregressive and q moving average terms.

$$y_t = \theta + \sum_{j=1}^{p} \alpha_p y_{t-p} + \varepsilon_t + \sum_{j=1}^{q} \beta_q \varepsilon_{t-q}$$

As we touched upon in a previous section about properties of the data, many financial time series are non-stationary. To be able to use ARMA modelling the time series needs to be stationary for the reasons described in the stationarity section. This can usually be obtained be taking the first difference one or several times of the non-stationary time series. If a time series needs to be differences *d* number of times to be stationary, it is said to be integrated of the *d*th order, I(*d*). If a time series needs to be differenced to obtain stationarity, it is incorporated in the ARMA framework, making it an ARIMA(*p, d, q*) framework. Though, our raw data series, that is the index and stock prices, is non-stationary, these are not the data that we are going to model. The return data we use are already (implicitly) differences and thereby stationary and thus we need no further differencing. With $d = 0$, we have an ARMA model.

Pure ARMA models let "*the data speak for themselves*"[84] in the way that y is explained only by lagged values of itself and stochastic error terms. Thus, they are not derived from any economic theory, which is often the basis of simultaneous-equation models. Following this, ARMA models are sometimes referred to as atheoretic models.[85]

An important tool in identifying ARMA (p, q) specification are the autocorrelation function (ACF) and the partial autocorrelation function (PACF), and the resulting correlogram (which we used to identify volatility clustering in a previous section), which plots the ACF and PACF against the lag length. The partial autocorrelation ρ_{kk} measures the correlation between y_t and y_{t-k}, after removing the effect of the intermediate lags between the two time periods, *t* and *t-k*. In

[83] Gujarati, Damodar N. (2003) p. 839
[84] Gujarati, Damodar N. (2003) pp. 838 – 839.
[85] Gujarati, Damodar N. (2003) pp. 839-840

the Identification part of Box-Jenkins methodology of model estimation we will use the ACF and PACF to estimate the ARMA specification for the present data.[86]

3.4 GARCH modelling

As described in the review of the literature, the ARCH(*p*) model was first developed by Engle in 1982 and was the first model to model and forecast conditional heteroscedasticity, that is time varying volatility conditioned on current information. Bollerslev extended the model to a generalised ARCH, GARCH(*p,q*), model where the model is also conditioned on its own lags of realized return.

3.4.1 ARCH

In the ARCH model ε_t is an unexpected asset return and defined as

$$\varepsilon_t = y_t - \mu_t(y_t)$$

, where y_t is the actual return in the current period and $\mu_t(y_t)$ the conditional mean of y_t given the information available in the previous period, $\mu_t(y_t) = E\{y_t|F_{t-1}\}$. Thus, the difference between the actual return and the conditional mean return is the unexpected return, ε_t . This is due the fact that the conditional mean return is the same as the expected return since $E\{\varepsilon_t|F_{t-1}\} = 0$.

It is assumed that $\varepsilon_t = z_t\sigma_t$, where z_t is a series of iid (independently, identically distributed) random variables with zero mean and variance 1, $z_t \sim N(0,1)$. This implies that conditioned on F_{t-1} , ε_t is distributed with 0 mean and σ_t^2 variance, $\varepsilon_t|F_{t-1} \sim D(0, \sigma_t^2)$.

$$\sigma_t^2 = \alpha_0 + \sum_{j=1}^{q} \alpha_j \, \varepsilon_{t-j}^2$$

, where $\alpha_0 > 0, \alpha_j \geq 0, j = 1, \dots, q-1, and\ \alpha_q > 0$.

This conditional variance defines an ARCH model and can be formulated as a AR(p) process for the squared error term, ε_t^2

$$\varepsilon_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \cdots \alpha_p\varepsilon_{t-p}^2 + u_t$$

[86] Gujarati, Damodar N. (2003) pp. 841-842

Simply put, the ARCH(p) process models the conditional variance of asset returns by saying that the conditional variance (σ_t^2) of ε_t at time t is determined by the squared unexpected asset returns in the previous periods, t - j. Hence, if a large unexpected increase or decrease in the asset returns occurred in one of the previous trading days (up to $t - q$), it will affect today's conditional variance. It should be noted that whether the unexpected shock is negative or positive it will have the same effect on volatility, as the unexpected return is squared, ε_t^2.[87] Adding the coefficients for the lagged squared error terms, $\alpha_1 + \cdots + \alpha_p$ gives a measure for the persistence in the conditional variance, which we will later use to measure volatility shocks and the speed of mean reversion.[88] In an information theory perspective the coefficient can be interpreted as the effect from yesterday's news on today's volatility.

3.4.2 GARCH

The generalised autoregressive conditional heteroscedasticity (GARCH) model extends the ARCH model so the conditional variance is also a function of its own lags, σ_{t-j}^2.

$$\sigma_t^2 = \alpha_0 + \sum_{j=1}^{q} \alpha_j \, \varepsilon_{t-j}^2 + \sum_{j=1}^{p} \beta_j \, \sigma_{t-j}^2$$

Similar to the description of an ARCH model as an AR(p) process of squared error terms, the GARCH model can be described as an ARMA(p,q) process of the squared error terms and its own lags. This feature has the effect that many of the properties of ARMA and GARCH processes are similar, and thus can be e.g. tested using similar methods. The conditional variance of the GARCH model has the property that the unconditional autocorrelation function of ε_t^2 can decay slowly, as the effect is captured by the lagged values of σ^2. For ARCH models, the decay rate is often too fast compared to what is in fact observed in real financial time series - unless lag q is long, meaning that the model includes many lagged values of ε^2. Thus the GARCH model provides longer memory of the conditional variance. Again this variable can be interpreted from an information theoretical perspective as the effect from news older than yesterday on today's volatility. Furthermore, the lag structure of the GARCH model is more flexible than in the ARCH

[87] Andersen et al. (2009) pp. 18-19
[88] Andersen et al. (2009) pp. 119-120

model, which can create problems with negative variance parameter estimates, if the ARCH model is created with many fixed lags, to satisfy the need for longer memory.[89]

In light of the short/long memory of ARCH/GARCH models, it may be noted that the GARCH model is a special case of an infinite-order ARCH model, ARCH(∞) and thus will need fewer lags than an ARCH model[90]

$$\sigma_t^2 = \alpha_0 + \sum_{j=1}^{\infty} \alpha_j \, \varepsilon_{t-j}^2$$

The most popular GARCH model has by far been the GARCH(1,1), with one lagged squared error term, ε_{t-1}^2 and one autoregressive variance term, σ_{t-1}^2, that is $q = j = 1$. With the condition that $\alpha_0 > 0, \alpha_j \geq 0, j = 1, \dots, q; \beta_j \geq 0,\ j = 1, \dots, p$..[91]

3.4.3 GJR-GARCH

A known feature of asset returns is that negative shock will have a larger effect on asset volatility than positive shocks. This is known as the leverage effect and was described in the subsection about division of the analysis period into subperiods (Section 1.10), where the index graphs for OMX S30 is much steeper in bear markets than in bull markets (Fig. 1.2), and also supported by the traditional standard deviation (Table 3.1). Furthermore, we found that the standard deviation in bear markets is greater than in bull markets, indicating that negative shocks/news in general have a larger impact on volatility than positive shocks/news. In the general GARCH model, the shock term from the conditional mean equation, ε_{t-1}^2, which goes into the conditional mean equation, is squared and thus has the same absolute value; hence a corresponding positive and negative shock will have the same effect on the conditional volatility. To adjust for this difference in shock impact, we employ the GJR-GARCH framework developed by Glosten, Jagannathan and Runkle (1993) (hence the name GJR).[92] In this model a dummy variable, I_{t-1}, is

[89] Bollerslev (1986) p. 2
[90] Andersen et al. (2009) pp. 19-20
[91] Andersen et al. (2009) p. 20
[92] Glosten et al. (1993)

added to the GARCH model. The dummy takes the value one, $I_{t-1} = 1$, if the shock term is positive , $\varepsilon_{t-1} > 0$, and the value zero, $I_{t-1} = 0$, if the shock term is negative, $\varepsilon_{t-1} < 0$.[93]

$$\sigma_t^2 = \alpha_0 + \sum_{j=1}^{q} \alpha_j\, \varepsilon_{t-j}^2 + \sum_{j=1}^{p} \beta_j\, \sigma_{t-j}^2 + \gamma \varepsilon_{t-j}^2 I_{t-1}$$

3.5 ARMA-GJR-GARCH modelling

The ARMA-GJR-GARCH model combines the ARMA proceses of the conditional mean equation with the GJR-GARCH processes of the conditional variance equation, so observations of y_t are generated by the ARMA processes and the variance generated by GJR-GARCH processes:

For conditional mean:

$$y_t = \theta + \sum_{j=1}^{p} \alpha_p y_{t-p} + \varepsilon_t + \sum_{j=1}^{q} \beta_q \varepsilon_{t-q}$$

$$\varepsilon_t | F_{t-1} \sim D(0, \sigma_t^2)$$

For conditional variance:

$$\sigma_t^2 = \alpha_0 + \sum_{j=1}^{q} \alpha_j\, \varepsilon_{t-j}^2 + \sum_{j=1}^{p} \beta_j\, \sigma_{t-j}^2 + \gamma \varepsilon_{t-j}^2 I_{t-1}$$

$$\alpha_0 > 0, \alpha_j \geq 0, j = 1, \dots, q; \beta_j \geq 0; I_{t-1} = 1\ (\varepsilon_{t-1} > 0), \quad j = 1, \dots, p$$

3.5.1 Including Volume and Open interest

As this study's focus is to investigate the effect of derivatives trading on the volatility of the underlying stock market, we need to add measures of derivatives trading activity to the equation for conditional variance. In the Data section we described how derivatives trading activity was measured by open interest and volume and how these proxies for hedgers and speculators, also called informed and unformed traders, respectively. The background for the this approximation is found in the traders characteristic, that the vast majority of speculators are day-traders who do not

[93] Some researchers use the value 1 for negative shocks and 0 for positive values. This approach does only alter the sign of the leverage effect dummy variable and leaves all other estimators unchanged. We will apply the GJR approach and will therefore obtain negative coefficients for negative shocks.

hold open positions overnight. Hence, the data for open interest, which indicates the number of open contracts as of the end of a trading day, likely reflects derivatives trading activity primarily used for hedging. Thus, volume (in conjunction with open interest) will indicate trading activities of speculators.

Furthermore, we divide both open interest and volume into expected and unexpected trading activity, allowing each component to have an independent effect on observed return volatility. Following the methodology of Pati (2008) we partition trading activity into expected and unexpected using a relevant ARMA framework. As described in the section regarding ARMA processes in relation to the conditional mean equation, the disturbance term ε_t proxies for unexpected asset return. Similarly, the residuals from an ARMA framework used on open interest and volume will specify the unexpected components of each:

$$VOL_t = \lambda_0 + \lambda_1 VOL_{t-1} + \lambda_2 \varepsilon_{t-1} + \varepsilon_t$$

$$OI_t = \lambda_0 + \lambda_1 OI_{t-1} + \lambda_2 \varepsilon_{t-1} + \varepsilon_t$$

With the actual and the unexpected values obtained for each variable, we define the expected volume and open interest as the difference between the two:

$$EXVOL_t = VOL_t - UNEXVOL_t$$

$$EXOI_t = OI_t - UNEXOI_t$$

The division into expected and unexpected trading activity allows more dimensions in our analysis. For open interest, the expected portion reflects the open interest at the beginning of the trading day; while unexpected open interest reflects unanticipated changes in net open positions of derivatives contracts. As a consequence, expected open interest is approximately equal to yesterday's level, and unexpected open interest will be roughly equal to the change in open interest during the trading day.

By including expected and unexpected components of open interest and volume in the conditional variance equation, we capture potential asymmetric responses of volatility to new information, caused by the difference in reaction by different types of traders. This would not have been possible with only GARCH processes in the conditional mean equation. The final model ARMA-GJR-GARCH model is defined by

For conditional mean:

$$y_t = \theta + \sum_{j=1}^{p} \alpha_p y_{t-p} + \varepsilon_t + \sum_{j=1}^{q} \beta_q \varepsilon_{t-q}$$

$$\varepsilon_t | F_{t-1} \sim D(0, \sigma_t^2)$$

For conditional variance:

$$\sigma_t^2 = \alpha_0 + \sum_{j=1}^{q} \alpha_j \, \varepsilon_{t-j}^2 + \sum_{j=1}^{p} \beta_j \, \sigma_{t-j}^2 + \gamma \varepsilon_{t-j}^2 I_{t-1} + \delta_1 UNEXOI_t + \delta_2 EXOI_t + \delta_3 UNEXVOL_t + \delta_4 EXVOL_t$$

$$\alpha_0 > 0, \alpha_j \geq 0, j = 1, \ldots, q; \beta_j \geq 0; I_{t-1} = 1 \; (\varepsilon_{t-1} > 0) \qquad j = 1, \ldots, p$$

As we touched upon earlier, the GARCH(1,1) model has by far been the most popular GARCH-type model in the econometric literature. Furthermore, it has proven difficult to find GARCH models with longer lag length that surpass the GARCH(1,1) model in describing volatility.[94] Consequently, we choose to use the GARCH(1,1) for the estimation of the conditional variance of asset returns.

In the section with empirical testing of the effect of derivatives trading activities on the volatility of the underlying asset, we conduct a variety of tests, described in the hypothesis section. Table 3.2. is an overview with the type of GARCH models employed together with the appropriate derivatives variables that will be used for the variance model of each test.

[94] Andersen et al. (2009) pp. 117-118

Table 3.2. Variance model in hypothesis testing

Test #	Variance equation
Test 1 (Index) **GARCH**	$\sigma_t^2 = \alpha_0 + \sum_{j=1}^{q} \alpha_j \, \varepsilon_{t-j}^2 + \sum_{j=1}^{p} \beta_j \, \sigma_{t-j}^2$
Test 2 (Index) **Test 6 (Asset)** **GJR-GARCH**	$\sigma_t^2 = \alpha_0 + \sum_{j=1}^{q} \alpha_j \, \varepsilon_{t-j}^2 + \sum_{j=1}^{p} \beta_j \, \sigma_{t-j}^2 + \gamma \varepsilon_{t-j}^2 I_{t-1}$
Test 3 (Index) **Test 7 (Asset)** **Extended GJR-GARCH**	$\sigma_t^2 = \alpha_0 + \sum_{j=1}^{q} \alpha_j \, \varepsilon_{t-j}^2 + \sum_{j=1}^{p} \beta_j \, \sigma_{t-j}^2 + \gamma \varepsilon_{t-j}^2 I_{t-1} + \rho_1 OI_{t-1} + \rho_2 VOL_{t-1}$
Test 4 (Index) **Test 8 (Asset)** **Extended GJR-GARCH**	$\sigma_t^2 = \alpha_0 + \sum_{j=1}^{q} \alpha_j \, \varepsilon_{t-j}^2 + \sum_{j=1}^{p} \beta_j \, \sigma_{t-j}^2 + \gamma \varepsilon_{t-j}^2 I_{t-1} + \delta_1 UNEXOI_t + \delta_2 EXOI_t + \delta_3 UNEXVOL_t + \delta_4 EXVOL_t$
Test 5 (Index) **Extended GJR-GARCH**	$\sigma_t^2 = \alpha_0 + \sum_{j=1}^{q} \alpha_j \, \varepsilon_{t-j}^2 + \sum_{j=1}^{p} \beta_j \, \sigma_{t-j}^2 + \gamma \varepsilon_{t-j}^2 I_{t-1} + \theta_1 futureOI_{t-1} + \theta_2 futureVOL_{t-1} + \theta_3 optionOI_{t-1} + \theta_4 optionVOL_{t-1}$

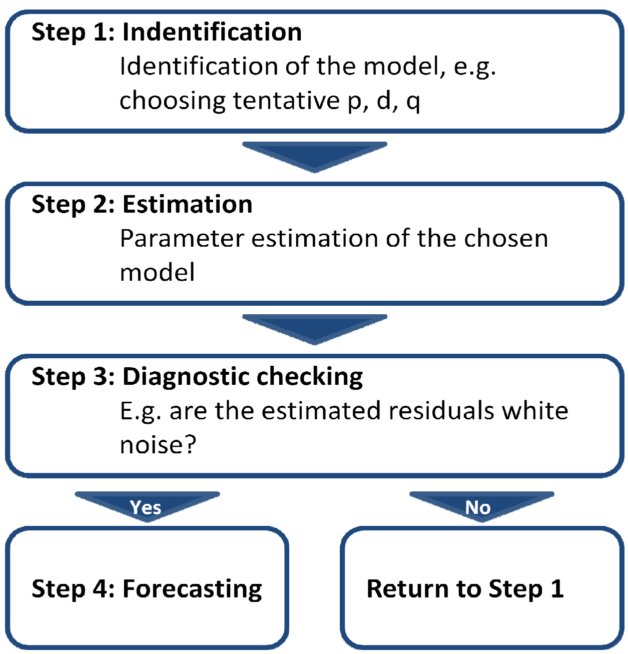
A more thorough analysis of the different variance models and how they fit the given test will be given in the analysis section together with the results of the tests.

While we rely on previous research and the general accepted fact that GARCH(1,1) is the best model in describing conditional volatility, to select the core model for describing volatility, we individually test the return series for each asset and the index to find the best fitting mean model. The specification of the ARMA processes in the mean model, with regard to number of lags of AR and MA terms, will be conducted in a preceding section, where the Box-Jenkins methodology is used to specify and evaluate the model and how it fits the relevant data.

3.6 Model specification

Based on our review of previous research and the statistical properties of our time series data, we have chosen a preliminary general ARMA-GJR-GARCH model for testing our hypotheses. However, we need to specify the elements of the model. More specifically, we need to identify the appropriate lags, *p* and *q*, which characterize our data in an ARMA-GJR-GARCH framework. For specifying a suitable model we apply the Box-Jenkins Methodology, which is a four step procedure for identifying and applying a relevant autoregressive model. The procedure is illustrated in figure 3.5. below and each step is described in the subsequent sections. The fourth step of the procedure is forecasting, and thus a forward-going application of the specified model. Forecasting, however, is out of scope for this paper, hence we will only describe and use step 1 through 3 in the Box-Jenkins methodology.

Figure 3.5. Illustration of the Box-Jenkins (BJ) Methodology[95]



Before specifying our ARMA-GARCH model, we will test for ARCH/GARCH effects in our daily return data. An ARCH model implies an autoregressive term in the squared residuals but will also show as autocorrelation in squared return, which was graphically observed in the section

[95] Gujarati, Damodar N. (2003); p. 841

about the statistical properties of the data. Hence, we do not expect the time series to be white noise but rather to exhibit autocorrelation in the squared return and thereby indicating volatility clustering or ARCH effects.

To test for white noise we apply the Ljung-Box Q statistic, which is defined by

$$LB = n(n+2)\sum_{k=1}^{m}\frac{\hat{\rho}_k^2}{n-k} \sim \chi^2 m$$

, which follows the chi-square distribution with *m* degrees of freedom, where *n* = sample size and m = lag length and $\hat{\rho}_k$ is the autocorrelation coefficient at *k* lag length.[96] The LB test is conducted in "bundles" of six lag lengths, where we report from lag 1 to 6 for each asset.

Table 3.3. Autocorrelation test for White Noise

Asset	Chi-square	To lag/DF	Pr > Chi-square	Autocorrelations					
OMX S30	895.90	6	<.0001	0.185	0.224	0.205	0.162	0.217	0.175
ABB LTD	15.40	6	0.0174	0.070	0.024	0.012	0.012	0.023	0.010
ASTRAZENECA	195.10	6	<.0001	0.171	0.125	0.158	0.093	0.058	0.076
ATLAS COPCO A	302.77	6	<.0001	0.113	0.108	0.101	0.124	0.131	0.162
AUTOLIV SDB	141.22	6	<.0001	0.130	0.060	0.071	0.098	0.063	0.068
ELECTROLUX B	183.16	6	<.0001	0.090	0.092	0.107	0.076	0.104	0.048
ERICSSON B	447.85	6	<.0001	0.202	0.168	0.105	0.080	0.106	0.131
HENNES & MAURITZ B	45.49	6	<.0001	0.050	0.049	0.037	0.045	0.021	0.059
HOLMEN B	85.99	6	<.0001	0.063	0.108	0.118	0.063	0.079	0.092
INVESTOR B	518.18	6	<.0001	0.153	0.180	0.195	0.113	0.149	0.076
LUNDIN PETROLEUM	379.80	6	<.0001	0.218	0.217	0.266	0.167	0.160	0.281
NOKIA CORPORATION	98.17	6	<.0001	0.051	0.080	0.081	0.053	0.073	0.067
SANDVIK	497.88	6	<.0001	0.144	0.148	0.173	0.130	0.160	0.120
SCA B	445.40	6	<.0001	0.132	0.159	0.161	0.137	0.123	0.109
SEB A	1284.92	6	<.0001	0.291	0.158	0.244	0.271	0.171	0.250
SKANSKA B	154.26	6	<.0001	0.109	0.069	0.094	0.076	0.084	0.052
SKF B	298.28	6	<.0001	0.172	0.135	0.107	0.077	0.108	0.113
STORA A	132.03	6	<.0001	0.156	0.086	0.141	0.179	0.122	0.165
STORA ENSO R	318.60	6	<.0001	0.132	0.147	0.172	0.140	0.120	0.102
SV. HANDELSBANKEN A	677.52	6	<.0001	0.213	0.190	0.274	0.293	0.225	0.229
TELE2 B	346.28	6	<.0001	0.105	0.215	0.116	0.099	0.091	0.101
TELIASONERA	71.25	6	<.0001	0.096	0.083	0.055	0.090	0.076	0.077
TRELLEBORG B	461.88	6	<.0001	0.136	0.148	0.148	0.120	0.147	0.142
VOLVO B	619.71	6	<.0001	0.198	0.165	0.160	0.171	0.131	0.146

[96] Gujarati, Damodar N. (2003) p. 808

The null hypothesis of the Ljung-Box statistic is the joint hypothesis that all the correlations up to lag k, in this case K = 6, is equal to zero, that is the series is white noise. Table 3.3. shows that the null hypothesis of no autocorrelation in squared return is clearly rejected for all assets. Only for ABB the null is not rejected on a 1 percent level, but is still significant at a satisfactory 2 percent level. It can be further seen that ABB has the lowest level of autocorrelation coefficients. These are displayed for lags 1 to 6 in the columns in the right side of the table.

3.6.1 BJ Step 1: Identification

The identification-process of the "correct" ARMA(p,q) model has been the subject of much econometric research. Broadly speaking, there exist two methodologies for identifying the p and q values. One is to the autocorrelation function and partial autocorrelation function to specify the most correct number of lags. The second method is to use information criterion, such as the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). In turn we will apply both methods to ensure that we have the best fitting model possible.

An important tool in identifying ARMA models in terms of lag length is the autocorrelation function (ACF) and the partial autocorrelation function (PACF). These autocorrelation functions are used to create correlograms, which merely are plots of the ACF and PACF against the lag length. We have already used the ACF correlograms in our detection of volatility clustering in section 3.1.1.

As the universal ACF is not observable, we will have to use a version based on a sample, which simply imply that the covariance and variance are based on sample-data of asset returns. It can be said that we use a realization of a stochastic process.[97]

The autocorrelation function (ACF) is defined as

$$\hat{\rho}_k = \frac{\hat{\gamma}_k}{\hat{\gamma}_0} = \frac{covariance\ at\ lag\ k}{variance} = \frac{cov(y_t, y_{t-k})}{var(t_t)} =$$

$$\frac{\sum_{i=1}^{n-k}(x_i - \bar{x})(x_{i+k} - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2}$$

[97] Gujarati, Damodar N. (2003) p. 808

, where $\hat{\rho}_k$ is the kth lag sample autocorrelation, $\hat{\gamma}_k$is the kth lag sample covariance and $\hat{\gamma}_0$ is the sample variance.[98]

Like ACF the PACF measures correlation between time series that are *k* periods from each other. However the PACF measures the correlation of time series *k* periods apart after taking out the effect of the autoregressive terms in-between the two observations.[99] This can be illustrated through the following regressions

$r_t = \phi_{0,1} + \phi_{1,1}r_{t-1} + \varepsilon_{1t}$

$r_t = \phi_{0,2} + \phi_{1,2}r + \phi_{2,2}r_{t-2} + \varepsilon_{2t}$

$\vdots \quad \vdots \quad \vdots$

$r_t = \phi_{0,k} + \phi_{1,k}r_{t-1} + \phi_{2,k}r_{t-2} \dots \phi_{k,k}r_{t-k} + \varepsilon_{kt}$

Here $\phi_{0,k}$ is a constant term, $\phi_{k,k}$ is the PACF coefficient (which we plot against the kth lag term in the PACF correlogram) and ε_{kt} is the error term. Through such regressions it is possible to find the PACF coefficient, $\phi_{k,k}$.[100] The sample can also be found by using the following function, where it can be seen that PACF is a function of its ACF[101]

$$\phi_{k,k} = \frac{\rho_k - \sum_{j=1}^{k-1} \phi_{k-1,j}\rho_{k-j}}{1 - \sum_{j=1}^{k-1} \phi_{k-1,j}\rho_j}$$

From the above regressions it can be seen that for an autoregressive model with *k* lags, AR(k), the PACF at lag k ($\phi_{k,k}$) should be significant. However, the PACF for lags above *k* ($e.g.\ \phi_{j,j}, j > k$) should be insignificant. Hence, there is a cut-off of partial autoregressive terms after lag *k*. From this it can be deduced that $\rho_1 = \phi_{1,1}$ as there are no intermediate lags in a AR(1) model and ACF and PACF must then necessarily be the same.[102]

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[98] SPSS Support;
http://support.spss.com/ProductsExt/SPSS/Documentation/Statistics/algorithms/14.0/acf_pacf.pdf
[99] Gujarati, Damodar N. (2003) pp. 840-845
[100] Tsay, Ruey S. (2005) pp. 40-41
[101] SPSS Support;
http://support.spss.com/ProductsExt/SPSS/Documentation/Statistics/algorithms/14.0/acf_pacf.pdf
[102] Tsay, Ruey S. (2005) pp. 40-41

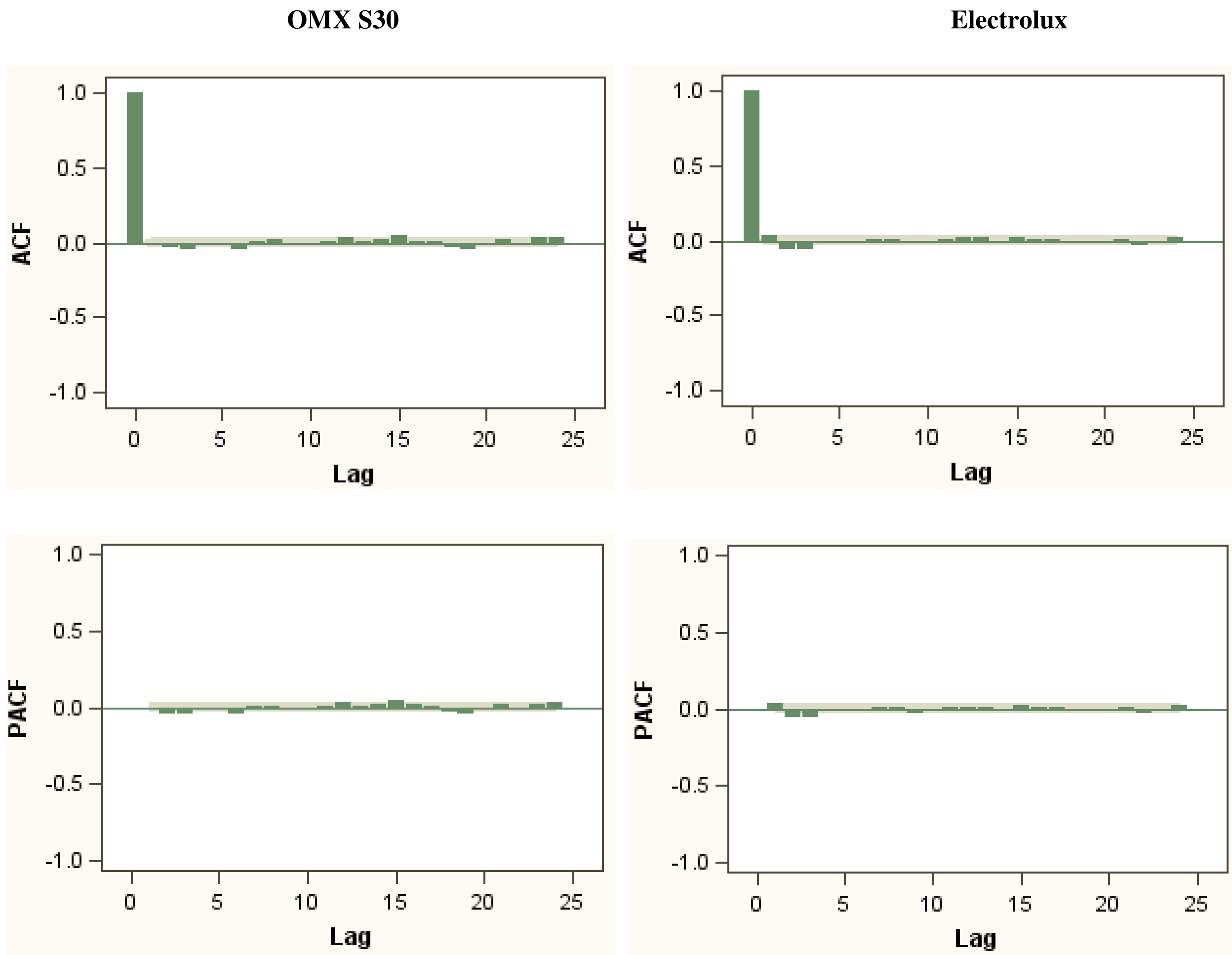
By plotting the sample ACF and PACF against their respective lag length, we will be able to fit ARMA processes to the stochastic time series. This is possible because different types of ARMA models exhibit different typical patterns in the ACF and PACF correlograms. We will use the general guidelines of theoretical patterns in ACF and PACF, which are displayed in Table 3.4.

Table 3.4. Theoretical pattern of ACF and PACF

Type of model	Typical pattern of ACF	Typical pattern of PACF
AR(*p*)	Exponential decay or damped sine wave pattern, or both	Significant spikes through lag *p*
MA(*q*)	Significant spikes through lag *q*	Exponential decline
ARMA(*p,q*)	Exponential decay	Exponential decay

We apply ACF/PACF framework on the usual asset examples OMX S30 and Electrolux. For OMX S30 neither ACF nor PACF show significant spikes in lag 1 and (thus) no exponential decline in the spike patterns, indicating no autocorrelation and no moving average terms, ARMA(0,0). For Electrolux we see slightly significant spikes in lags 1 through 3 in both ACF and PACF, indicating that we could either be dealing with an ARMA(3,0) or and ARMA(0,3) process. However it is difficult to determine which one from the correlograms, which can be seen from the below Figure 3.6.

Figure 3.6. ACF and PACF correlograms of sample autocorrelation in daily returns series



The Electrolux example shows the difficulty in estimating the precise p and q if relying only on the ACF/PACF methodology. Furthermore, ACF/PACF has trouble estimating models with both AR and MA terms. Therefore, we apply a second method for order-identification of the ARMA process, which is the use of information criteria.

The most widely used information criteria for identifying number of lags in ARMA processes are the Akaike information criterion (AIC) developed by Akaike (1973) and the Bayesian information criteria (BIC) by Schwarz (1978).

The AIC is a likelihood function and is defined as[103]

[103] Tsay, Ruey S. (2005) pp. 41-42

$$AIC = \frac{-2\ln(likelihood)}{n} + \frac{2r}{n}$$

The likelihood term is estimated by the maximum likelihood function (which will be described more in-depth in the next subsection, as we use it for parameter estimation), *r* is the number of parameters and *n* is the sample size (which this notation of AIC normalizes for. However, the AIC model used by SAS does not). The first part of the AIC model above is a *goodness of fit* measure, indicating how well the model fits the actual data. The second part of the model is a penalty function of the model as it penalizes the model under evaluation based on the number of parameters suggested by the model.[104]

When using AIC for model selection one has to select a number of candidate models to fit the data. AIC is then computed for each of the models in scope, and the model with the smallest AIC is the one that best fit "*the unknown reality that generated the data"*[105] from the sample of evaluated models. Hence the AIC framework is not based on hypothesis testing but on simply comparison. When comparing the AIC values of different models, it is not the absolute but the relative sizes that should be the basis for selecting the best model out of the evaluation set.

Naturally the procedure of selecting a best model out of an evaluation set has the inappropriateness that even if none of the candidate models in the set is very good, the AIC framework will choose the best out of the poor models. As the relative best model is not automatically very good in absolute terms, it is necessary to be very meticulous in selecting the candidate models for the evaluation set.[106] By applying the ACF and PACF method we select the candidate models for the evaluation set.

The Bayesian information criterion is very similar to the AIC and defined as follows

$$BIC = -2\ln(likelihood) + rln(n)$$

Like in AIC the first part measures *goodness of fit*, while the second term is a penalty term. As before *r* indicates the number of parameters and *n* is the sample size (which opporsitely AIC is accounted for in SAS' calculations). The biggest difference compared to AIC is the factor of the

[104] Tsay, Ruey S. (2005) pp. 41-42
[105] Tsay, Ruey S. (2005) pp. 41-42
[106] Tsay, Ruey S. (2005) pp. 41-42

penalty term. For AIC it is 2, while it is $\ln(n)$ for BIC. As for AIC, the selection criteria for BIC is the lowest BIC value, thus the penalty term means that BIC tend to select models with few parameters (p and q) when the sample size is large.[107] As described in the subsection about model selection methodology a desirable model feature is parsimony and we therefore chose to use the BIC for the numerical evaluation of model selection as it will tend to select lower order ARMA models.

For OMX S30 and Electrolux different combinations of p- and q-values between 0 and 5 have been tested and are reported in Appendix 4 in a 6 by 6 matrix, where the lowest BIC-value is selected for each. For OMX S30 our model suggestion from ACF/PACF ARMA(0,0) is confirmed and we chose this model for our mean equation. Based on ACF/PACF correlograms Electrolux could be both an ARMA(3,0) and an ARMA(0,3) process. From the BIC matrix we find the best model to be ARMA(0,3) which is chosen for the Electrolux mean equation. However, it should be mentioned that based on BIC values ARMA(3,0) would be the second best model to describe Electrolux's return. Similar tests have been conducted on the remaining 22 assets and are reported Table 3.5. below.

[107] Tsay, Ruey S. (2005) pp. 41-42

Table 3.5. Model Specification

Asset	# AR terms	# MA terms	Final model
OMX S30	0	0	GJR-GARCH(1,1)
ABB LTD	0	1	ARMA(0,1)-GJR-GARCH(1,1)
ASTRAZENECA	0	0	GJR-GARCH(1,1)
ATLAS COPCO A	0	0	GJR-GARCH(1,1)
AUTOLIV SDB	0	1	ARMA(0,1)-GJR-GARCH(1,1)
ELECTROLUX B	0	3	ARMA(0,3)-GJR-GARCH(1,1)
ERICSSON B	0	1	ARMA(0,1)-GJR-GARCH(1,1)
HENNES & MAURITZ B	1	2	ARMA(1,2)-GJR-GARCH(1,1)
HOLMEN B	0	0	GJR-GARCH(1,1)
INVESTOR B	0	0	GJR-GARCH(1,1)
LUNDIN PETROLEUM	0	0	GJR-GARCH(1,1)
NOKIA CORPORATION	0	0	GJR-GARCH(1,1)
SANDVIK	0	0	GJR-GARCH(1,1)
SCA B	0	0	GJR-GARCH(1,1)
SEB A	0	3	ARMA(0,3)-GJR-GARCH(1,1)
SKANSKA B	0	0	GJR-GARCH(1,1)
SKF B	0	0	GJR-GARCH(1,1)
STORA A	0	1	ARMA(0,1)-GJR-GARCH(1,1)
STORA ENSO R	0	1	ARMA(0,1)-GJR-GARCH(1,1)
SV. HANDELSBANKEN A	1	1	ARMA(1,1)-GJR-GARCH(1,1)
TELE2 B	0	0	GJR-GARCH(1,1)
TELIASONERA	0	0	GJR-GARCH(1,1)
TRELLEBORG B	1	0	ARMA(1,0)-GJR-GARCH(1,1)
VOLVO B	0	0	GJR-GARCH(1,1)

The models used for each asset are presented in the column far right in Table 3.5. As we described earlier all assets have a GJR term (though not present in all tests) and GARCH(1,1) in the variance equation, while the models vary in number of ARMA processes in the mean equation to fit the return series of each asset.

3.6.2 BJ Step 2: Estimation

The non-linear properties of the parameters of our chosen econometric model impose some limitation of the estimation of the parameters of the model and restrict us from using the widely used *Ordinary Least Squares* method (OLS). Moreover, the choice of the Student-t distribution to account for excess leptokurtosis also limits our estimation method to non-linear in the parameters estimation methods. The estimation method of Maximum Likelihood (ML) is therefore chosen and accounted for in the following section.

The distinctive difference between the OLS - and the ML method is that the former is minimizing the sum of the squared error term (the stochastic element) while the latter maximizes the probability of obtaining the unknown parameters with respect to the dependent times series (in our case the conditional variance), given some assumptions about the shape of the density function.[108] Thus the Maximum Likelihood Estimators (MLE) are the closest fit for the parameters given the observed data. Especially the property of taking the density function into account is a desirable property in our case. Furthermore, it has been shown that the likelihood function of which the MLEs are derived reflect all the useful information about the parameters in the ARMA-GJR-GARCH model.[109] The fact that our model contains more than one variable makes the optimization process of the parameters difficult and has no analytical solution. The MLE therefore provides the best unbiased estimators. Below we describe the ML estimation for a general GARCH(1,1) process using Quasi-Maximum Likelihood Estimation. The existence of autoregressive orders in mean equation as well as a non-normal probability distribution makes the ML estimation quite troublesome. Thus, we have described the estimation method applied by the SAS software package for this type of estimation in Appendix 5.

The assumption of the QMLE is to maximize the likelihood function under the assumption that the η_t(the noise term) is Gaussian. The term ϵ_t is then Gaussian conditioned on past values of ϵ's and σ's which is a very tractable form for the maximizing the likelihood function.

Based on the initial values $\epsilon_0, \dots., \epsilon_{1-q}, \tilde{\sigma}_0^2, \dots, \tilde{\sigma}_{1-p}^2$, we can define the sample conditional variance recursively

$$\tilde{\sigma}_t^2 = \tilde{\sigma}_t^2(\theta) = \omega + \sum_{j=1}^{q} \alpha_p \, \epsilon_{t-1}^2 + \sum_{j=1}^{q} \beta_q \, \tilde{\sigma}_{t-j}^2$$

for t = 1,…,n. Because of the initial values the function is not stationary but rather as an approximation of the stationary general function for σ_t^2 under the assumption $\sum_{j=1}^{p} \beta_j$, where $\sigma_t^2(\theta_0) = h_t$

[108] Gujaranti (2003); pp. 112 – 113
[109] Tsay (2005); pp. 367 – 368

$$\sigma_t^2 = \sigma_t^2(\theta) = \omega + \sum_{j=1}^{q} \alpha_p \, \epsilon_{t-1}^2 + \sum_{j=1}^{q} \beta_q \, \sigma_{t-j}^2$$

The likelihood function that is maximized for the observations $\epsilon_1, \dots, \epsilon_n$is the function

$$\tilde{L}_n(\theta) = \prod_{t=1}^{n} \frac{1}{\sqrt{2\pi\tilde{\sigma}_t^2}} \exp\left(-\frac{\epsilon_t^2}{2\tilde{\sigma}_t^2}\right)$$

A quasi maximum likelihood estimate of the true $\theta_0$is a solution, denoted as $\hat{\theta}_n^{QML}$of

$$\hat{\theta}_n^{QML} = arg \max_{\theta \in \ominus} \tilde{L}_n(\theta) \, \mathrm{arg}\, max = \mathrm{arg} \min_{\theta \in \ominus} \tilde{I}_n(\theta)$$

, where

$$\tilde{I}_n(\theta) = n^{-1} \sum_{t=1}^{n} \tilde{l}_t \qquad and \qquad \tilde{l}_t = \tilde{l}_t(\theta) = \frac{\epsilon_t^2}{\tilde{\sigma}_t^2} + log\tilde{\sigma}_t^2$$

Let $\mathcal{A}_\theta(z) = \sum_{i=1}^{q} \alpha_i z^i$ and $\mathcal{B}_\theta(z) = 1 - \sum_{j=1}^{p} \beta_j z^j$ with $\mathcal{A}_\theta(z) = 0$ if $q = 0$and $\mathcal{B}_\theta(z) = 1$ if $p = 0$. It is shown that under the following assumptions:

Assumption 1	$\theta \in \ominus$ and $\ominus$is compact
Assumption 2	$\gamma A_0 < 0$ and $\forall\, \theta \in \ominus$, $\sum_{j=1}^{p} \beta_j < 1$ (strict stationarity is only enforced on the true value of the parameter)
Assumption 3	η_t^2 has a non-degenerate distribution with $E\eta_1^2 = 1$
Assumption 4	$p > 0$, $\mathcal{A}_{\theta 0}(z)$ and $\mathcal{B}_{\theta 0}(z)$ have no common root, $\mathcal{A}_{\theta o}(1) \neq 0$and $\alpha_{0q} + \beta_{0p} \neq 0$

the QMLE is strongly consistent,

$$\hat{\theta}_n^{QML} \to \theta_0, \quad as \quad n \to \infty$$ [110]

[110] Andersen et al (2009) p. 90-91

The Maximum Likelihood Estimates has some limitations. One of them is that the used densities are not uniquely defined, which means that the likelihood criterion which lays the basis for MLE is not uniquely defined. Hence, there might not be a solution to the maximization problem, or conversely, there might be more than one solution. As the number of variables in a model increases, ML has increased difficulty in maximizing the likelihood function. This has manifested in convergence problems in the likelihood function in SAS and caused some parameters to be "Biased". This has been apparent in models with relatively many variables and in data for single stocks. However, we will use the sign of the coefficient estimates in the analysis part of this thesis, but not include the biased results in the overall assessment of the found results.

3.6.3 BJ Step 3: Diagnostic checking

The third step of the Box-Jenkins methodology is to conduct diagnostic checking on the selected model. While the volatility model later will be used in a number of different variation, the diagnostic checking will here be conducted on the core ARMA(p,q)-GJR-GARCH(1,1) model, to see if it is a reasonable fit for the return data on the Swedish stock market. Later in the empirical analysis goodness-of-fit estimates such as Breusch-Godfrey's serial correlation LM test and Ljung-Box Q test will be reported to evaluate the various models ability to fit the data.

The diagnostic checking tests are conducted on the estimated standardized residuals, which should have the properties of classical regression models, i.e. they should be white noise. This implies that they should display no autocorrelation, no conditional heteroscedasticity and their distribution should be equivalent to the error distribution used in the model estimation.[111] In the following each of these properties will be presented for the ARMA(p,q)-GJR-GARCH(1,1) model for OMXS30 and Electrolux. In our analysis part we will report results for all the assets and the index as well.

To test for serial correlation in the standardized residuals, $\frac{\hat{\epsilon}_t}{\hat{\sigma}_t}$, we apply Breusch-Godfrey's serial correlation Lagrange Multiplier test. It uses a Lagrange Multiplier (LM) test based on the auxiliary regression

$$\hat{\epsilon}_t = \alpha_0 + \alpha_1 \hat{\epsilon}_{t-1} + \cdots + \alpha_p \hat{\epsilon}_{t-p} + v_t$$

[111] Andersen et al. (2009) p. 127

to test for serial correlation in estimated error terms. We test the null hypothesis that there are no autocorrelation up to lag p, H_0: $\alpha_1 = \alpha_2 = \cdots = \alpha_p = 0$. SAS operates with $p = 4$, which is used.

The test statistic $LM = T * R^2$ has an asymptotic chi-square distribution with p degrees of freedom, where T represents the sample size and R^2 is obtained from the auxiliary regression above. If the null hypothesis is accepted, there would be no autoregressive effect in the error terms.[112] In Table 3.5. below is the test results for OMXS30 and Electrolux displayed, where OMXS30 with a LM test value of 0.67 and a corresponding probability of 41.25 percent cannot reject the null hypothesis of white noise; that is there is no serial correlation in the error term. Opposite OMXS30, Electrolux displayed ARMA processes in its mean model, which we try to capture by fitting an ARMA(0,3) process to its mean model. However, Electrolux still display series correlation in the residuals and we can reject the white noise hypothesis. Following, the Box-Jenkins methodology we try to fit another mean model to Electrolux in hopes of obtaining a better specified model and residuals with nicer properties. Returning to the information criteria, we select the model with the second lowest information criterion, which is found to be an ARMA(3,0) which is fitted to the Electrolux data series. The LM results are displayed in parenthesis in Table 3.6. Though the LM value are smaller and ARMA(3,0) captures more autocorrelation than ARMA(0,3), it is not enough to accept the hypothesis of white noise. For Electrolux we progress with the ARMA(0,3)-GJR-GARCH(1,1) model based on our initial selection criteria.

Table 3.6. Test of residuals

	OMXS30		Electrolux	
Test	**Test value**	**Pr > Test value**	**Test value**	**Pr > Test value**
LM	0.67	0.4125	8.59 (6.40)	0.0034 (0.0114)
LB Q (6)	3.52	0.7413	8.68	0.1924
LB Q (12)	6.86	0.8666	11.43	0.4927
LB Q (18)	11.94	0.8506	14.19	0.7163
LB Q (24)	16.87	0.8542	15.21	0.9145

To test for remaining ARCH effects in the data, we apply the Ljung-Box Q autocorrelation test on the squared standardized residuals, $\frac{\hat{\epsilon}_t^2}{\hat{\sigma}_t^2}$, as ARCH effects manifest itself as autocorrelation in

[112] Andersen et al. (2009) pp. 115-122

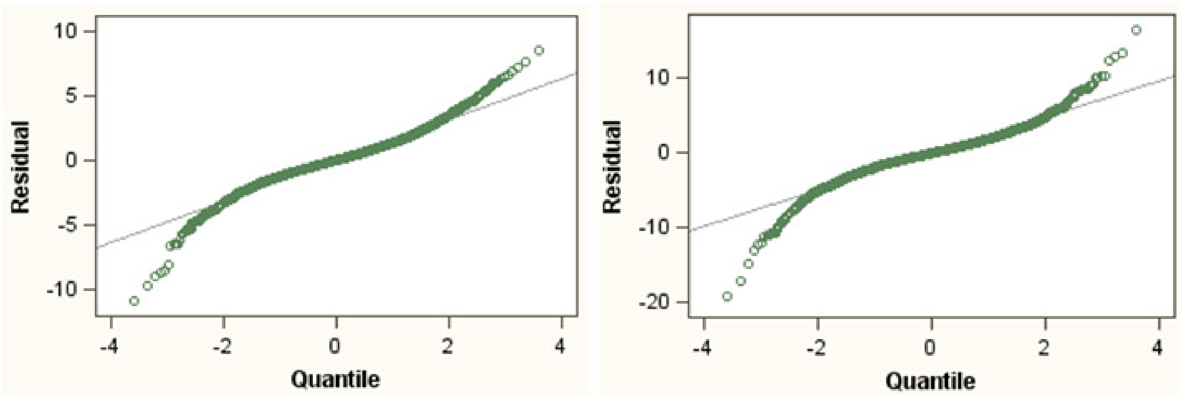
squared residuals. The test is similar to the one that was initially used in detecting volatility clustering in the identification step of Box-Jenkins, only then it was applied on squared return and not squared residuals. However, the methodology of the test is the same; it tests the joint hypothesis that all the correlations up to lag k is equal to zero, which would make them white noise. The LB Q statistics are presented in bundles of lags up to lag 24 and are displayed in the lower part of Table 3.5. for OMXS30 and Electrolux. For neither of the two asset examples we are able to reject the white noise hypothesis at any lags; as opposed to the test results in the identification step, where we rejected the null for all assets. Hence the GARCH(1,1) has captured the conditional variance of the return data on a satisfactory significance level. For the test in the empirical section, we will only report the test value and corresponding probability for lags up to $k = 6$.

Another goodness-of-fit test which is often applied in testing for remaining ARCH effect is Engle's LM statistic, which is similar to the Breusch-Godfrey's LM autocorrelation test but with squared standardized residuals in the auxiliary regression. Thus it tests for $H_0: \alpha_1 = \alpha_2 = \cdots = \alpha_p = 0$ in the regression $\hat{\epsilon}_t^2 = \alpha_0 + \alpha_1 \hat{\epsilon}_{t-1}^2 + \cdots + \alpha_p \hat{\epsilon}_{t-p}^2 + v_t$, that is no serial correlation in squared standardized residuals and hence no ARCH effects. However, it has not been possible to apply Engle's LM statistic on the selected model in SAS, why we use the Ljung-Box Q test for remaining ARCH effects.

The last part in the diagnostic checking is evaluating the residual distribution. It should match the specified error distribution stated in the model, which in this case is the student's t distribution.

Figure 3.7. QQ-plot for OMXS30 and Electrolux residuals

OMX S30 **Electrolux**



The residuals should somewhat follow the respective lines in Figure 3.7. above it the data had been normally distributed. However, as touched upon earlier, the return series does more resemble a student's t-distribution than a normal distribution, which is similar to the normal distribution, and even more so when the sample size grows bigger, but with fatter tails than the normal distribution. The higher number of "extreme" observations, which is the cause of the fat tails in both ends in the bell shaped distribution curve, it also that causes the shape of the residual plot in the QQ-plot above (Fig. 3.7.), as the shape indicates symmetric long tails at both ends.[113] Thus, from graphical inspection, we conclude that the residuals from our estimated ARMA(*p,q*)-GJR-GARCH(1,1) model are correctly distributed and in accordance with the t-distribution.

In the previous section we have specified the core ARMA(*p,q*)-GJR-GARCH(1,1) model for each of the assets under investigation. For each asset we stepwise extend the model to include more detailed measures of derivatives trading activity, trading volume and open interest (expected and unexpected), in order to enable measurement of their effect on the volatility of the underlying asset. The parameter estimation along with the measures for diagnostic checking are estimated, reported and interpreted in section 4.

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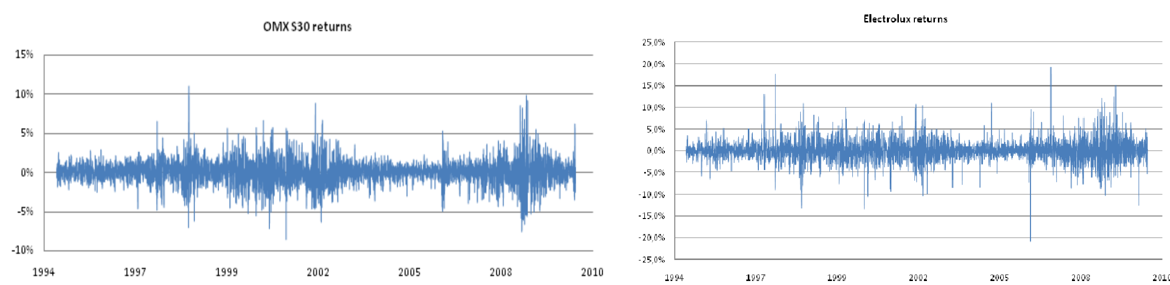
[113] SAS Institute "Are histograms giving you fits?"p. 5

3.6.4 Limitations of the ARMA-GJR-GARCH model and critique

In the following we will discuss the limitations of the ARMA-GJR-GARCH model we have chosen in relation to our problem statement. Hereafter we will include competing models as alternatives for measuring the conditional variance of financial time series.

Although the ARMA-GJR-GARCH model include a dummy variable to correct for the asymmetric leverage effect in financial time series, it still has difficulties in capture all the effect from irregular and extreme market conditions such as financial market crashes and subsequent rebounds. Extreme market condition often crates outliers in the data set. We have identified these outliers as spikes in the following Figure 3.8. for the OMXS30 index and Electrolux.

Figure 3.8. Identification of spikes and outliers



Here both outliers and volatility clustering can be identified. The outliers represented as spikes are pronounced around periods of volatility clustering, which support our finding of the existence of the leverage effect. Furthermore, the index data exhibit more clearly the stylized facts of financial time series than the Electrolux share data. Here outliers can be identified in periods without volatility clustering, which are explained by company specific event that affect the share price substantially. We will in our analysis part ignore the existence of outliers due to a large number of observations on both index level and for specific companies, which for the whole period amount to 3.902 observations. The effect from outliers and extreme market conditions is therefore weak in the overall period and distributed evenly in the time interval. In addition, the division of the whole period into subperiods will create periods of higher volatility clustering and more outliers than others (e.g. in the recent period from 2009 to present), while other periods will exhibit stable market conditions (e.g. in the period from 2002 to 2007). Again the large number of observations in each sub-period allows us to ignore the outliers in extreme market conditions. A possible solution for the outliers has been proposed for SV-models, which have the possibility to include a diffusion parameter.[114] This fact is more relevant for other asset types than stocks and their derivatives due to the relatively small amount of spikes in the data series (e.g. electrical prices and electrical derivatives).[115] We therefore find that the minimal number of observed outliers only limited will affect our estimation results. Also most of the effect from extreme market conditions is found to be captured by the GJR-GARCH in the dummy variable. We will therefore not carry any data mining processes out to correct for extreme and unstable market conditions in the analyzed period.

Another limitation of the GARCH model is the inability to capture all the fat tail behaviour of stock returns when the normal cumulative distribution is employed as distribution in the estimation of the model. By using a student-t distribution we take this limitation into account. In sum, the use of a dummy variable in the second moment equation of volatility (the GARCH equation for the conditional variance) for a large sample and the use of the student-t distribution in the estimation method for our model, should correct for the identified leptokurtosis in the data.

3.6.5 Competing models

In the following we will treat competing models to the ARMA-GARCH model we have chosen. We will focus on the Stochastic Volatility Model (SVM) and Vector Autoregressive (VAR) models, which are the two most widely used models for capturing the time-varying volatility properties of high frequency financial time series data.

3.6.5.1 Stochastic Volatility Models

Together with the GARCH-type model family the SV models are the most used to modeling the time-varying volatility of financial time series.[116] As for the GARCH-type models SV models are also able to capture volatility clustering, which is a recognized stylized fact of the statistical properties of asset returns.[117] In this perspective the two models describe the volatility pattern in financial time series the same way. The distinctively differences between the GARCH-type models and SV-models is that the GARCH-type models seeks to explain the stochastic behaviour of volatility from all the available information from the past and a single error term. In our case we use return series, open interests and volume to explain the stochastic behaviour of financial

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[114] Sørensen (2009); pp. 532 – 551
[115] Cartea & Figueroa (2005); pp. 317 – 320
[116] Shephard & Andersen (2009); pp. 233 – 234
[117] Cont (2000) p. 224

time series. In contrary, SV-models are non-deterministic in all means and include a second stochastic element in explaining the volatility and in forecasting futures volatilities. The non-deterministic element enters the model as a second error term (an unobserved latent variable) and is generated by a random walk process, which by definition is unpredictable and often generated by Marco Chain Monte Carlo statistical inference.[118]

One major advantage of the SV-model is the ability to deal with continuous time series and thus creating a continuous time volatility model, which is of great relevance in many applied financial situations.[119] Since we use daily data in our estimation we will not touch upon continuous time SV-models, but only include discrete SV-models that use high frequency data with identical intervals between each observation, such as daily observations. The standard SV-model[120] includes two stochastic processes and is usually defined from their first and second moments as follows:

$$y_t = \exp\left(\frac{h_t}{2}\right) u_t, \qquad u_t \sim N(0,1)$$

$$h_t = \mu + \emptyset(h_{t-1} - \mu) + \eta_t, \qquad \eta_t \sim N(0, \sigma_\eta^2)$$

Where y_t is the log-return at time t, and h_t denotes the log-volatility that follows an AR(1) stationary process. u_t and η_t are the stochastic elements and Gaussian White Noise sequences.

The solution to the above SV-model is more difficult to find than for the GARCH-type of models due to their open form. Thus closed form solutions through any maximum likelihood estimation are not possible, and computation of the model often requires extensive simulations to replicate the two stochastic elements of the model. The reason for the open form is found in the impossibility of directly observe the density function of the relevant distribution, which leads to difficulties. This is not the case for the GARCH models, where estimation of the parameters can be done by the maximum likelihood approach with a predetermined density distribution.

[118] Hautsch & Yanguoyi (2008) pp. 2 – 3.
[119] Examples are given in Juttmann (2007) who mention daily option pricing, daily hedging activities, Calculation of Black-Scholes options pricing and various trading strategies involving volatility measures.
[120] Taylor (1992) p. 37

The SV-models are like the GARCH-type models able to deal with various stylized facts of financial time series through extensions of the above model. These facts include fat tail behaviour and volatility clustering (leptokurtosis), jump components in the time series, the leverage effect and long memory of volatility levels (persistence in the volatility).[121] The SV-model is found to be superior to the GARCH-type of models in describing these facts in some researches, while other researchers find the GARCH models to provide the best fit of the stylized facts of stock returns.[122] Thus we also find ambiguity in this field of study, and can conclude that proponents of a particular model to describe realized volatility often is based on that researchers believes and previously experiences. However, the increasing capacity in computation of SV-models due to the use of new advanced databases and methods has the recent years shifted the view in favor of SV proponents. Furthermore, the second stochastic variable included in the SV-models have proved to provide at better fit for describing the pattern of financial time series than other competing models in out-of-sample estimation.[123]

We have chosen to use the GARCH-type of models due to its lower complexity in the estimation of the parameters despite of the above mentioned advantages of the SV-models. Also the availability of an observed density distribution is a critical and missing element in the SV-models, which complicate the estimation process substantially. Finally, since we estimate in-sample volatilities and not forecast future volatilities, GARCH models often provide results as accurate as the SV-model. The forecasting abilities of the chosen model are thus irrelevant to answer the scope of the problem statement.

3.6.5.2 Vector Autoregressive models (VAR)

Vector Autoregressive models are another type of models to find the co-integration between selected financial times series. Its origin dates back to macroeconomic theory[124]and have been widely employed within political science. Its application within volatility is not as popular as for the GARCH-type of models and SV-models. Recent examples of its application within the field stochastic volatility include open interest and volume as variables to test for the effect on the

[121] Hautsch & Yangguoyi (2008); pp. 4 – 9
[122] Hol (2003). P. 4 and Poon & Granger (2003); pp. 506 – 534.
[123] Hol (2003). pp. 7 – 26
[124] Sims (1980)

underlying spot volatility from index futures trading.[125] Even though the model is applicable on relevant stochastic volatility issues it contains quite a few limitations. The most prominent limitation is the impracticable property of taking the stylized facts of financial time series into account in standard VAR models (such as ARCH processes).[126] These properties are only possible to incorporate with difficulties.

We recognize the existence and their advantages in other financial time series studies, but will not come into further details due to the above identified limitations of the VAR-type of models in relation to our investigation.

3.7 Part conclusion on empirical modelling

From investigating the stylized facts of the data used we found evidence of volatility clustering, leptokurtosis in the distribution and mean-reverting return series. These stylized facts of financial time series also support our choice of a GARCH-type model. An Autoregressive Moving Average (ARMA) element was added to remove the predictability associated with lagged returns, while a dummy to correct for the leverage effect was included. The ARMA process was investigated for each asset and the index to take into account individual statistical properties of each asset. Thus the GARCH-type model that best captures the characteristics of the data and employed in the rest of the thesis was an ARMA(p,q)-GJR-GARCH(1,1) model.

4 Empirical test and results

4.1.1 Test 1 & 2 – results and comments

To support our choice of model and the inclusion of the dummy variable to replicate the leverage effect we conducted two GARCH models. In the first model the leverage effect dummy is excluded while the second includes the dummy. The found results are summarized in the Table 4.1., where the standard GARCH(1,1) takes the form: $\sigma_t^2 = \alpha_0 + \sum \alpha_1 \varepsilon_{t-1}^2 + \sum \beta_1 \sigma_{t-1}^2$, while the GJR-GARCH(1,1) has the form: $\sigma_t^2 = \alpha_0 + \sum \alpha_1 \varepsilon_{t-1}^2 + \sum \beta_1 \sigma_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1}$. Also the Lagrange Multiplier Test and the Ljung-Box Q(6)

[125] Ferris et Al. (2002). 369 – 372
[126] Ferris et Al. (2002). 369 – 372

test for remaining autocorrelation and measure the goodness-of-fit respectively are given in the table.

Table 4.1. Test 1 & 2 results. GARCH vs. GJR-GARCH

TEST 1&2	GARCH(1,1)		GJR-GARCH(1,1,)	
	Estimates	P-STAT	Estimates	P-STAT
Intercept	0.098194	<.0001	0.067428	0.0003
ARCH 0	0.016474	0.0006	0.023794	<.0001
ARCH 1	0.073181	<.0001	0.1195	<.0001
GARCH	0.908029	<.0001	0.906398	<.0001
GJR	-	-	0.09615	<.0001
TEST LM	5.62	0.0178	0.67	0.4125
LB-Q (6) test	8.68	0.1927	3.52	0.7413

From the above estimation results we observe weakly stationarity for both the GARCH(1,1) model and the GJR-GARCH(1,1) model. For the GARCH(1,1) model weakly stationarity is fulfilled from the proposition[127]: $\alpha_1 + \beta_1 < 1$ (0.908029 + 0.073181 = 0.98121), while the weakly stationarity is present in the asymmetric GJR-GARCH(1,1) model when the proposition[128] $\alpha_1 + \beta_1 + \frac{1}{2}\gamma < 1$ (0.906398 + 0.1195 + ½ *-0.09615 = 0.977823) is fulfilled (this is also referred to as co-variance stationarity in some research).[129] The fulfilled conditions are also a sign of mean-reverting return series as proved in the statistical properties of the data.

The GARCH coefficient is found to be significant for both models and exhibit similar sizes around 0.9, which indicate the effect from news arrived to the market participants before yesterday. The high absolute value of the GARCH coefficients point to a slow decaying volatility following a shock, which also support our finding of volatility clustering. In contrast, small GARCH coefficient relative to the ARCH coefficient indicates shorter persistence in the volatility, which would contradict our finding in the section where we investigated the statistical properties of the data. Thus the high persistence in volatility is supported by the GARCH models as predicted.

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[127] Handbook of Financial Time Series (2009); pp. 44 – 51.
[128] Ling & McAleer (2002). P. 112
[129] Pati (2007). Pp. 35 – 36.

Also the ARCH coefficients are found to be significant for both models, while the relative small absolute value of the coefficients indicates few unexpected spikes in the data series as described in an earlier section.

The asymmetric element in the GJR-GARCH model is highly significant and negative. The asymmetric element in financial time series is captured by a dummy variable that indicates that positive news has less impact on the volatility than negative news, or conversely, that negative news has a larger effect on volatility than positive news. We will use the latter description of the dummy variable in the rest of the interpretation of our result throughout this thesis to simplify its meaning. A negative coefficient for the dummy variable thus implies larger effect from negative news than from positive news and will be destabilizing on the volatility.

The employed Lagrange Multiplier Test (LM) for White Noise and autocorrelation is significant at a 5% level for the GARCH model, which indicates that not all the autocorrelation in the return series is captured by the model. The Ljung-Box Q (LB-Q(6)) test for autocorrelation in the squared residuals is found insignificant, which is an appropriate sign of the goodness of fit of the model. We can thus conclude that the GARCH model is an appropriate model for describing the analyzed data, but that not all the ARCH effects are captured.

The LM Test for the GJR-GARHC model is found to be insignificant, which indicates that persistence in the volatility is satisfactorily captured and that the models are well-specified. The fact that the LM Test turns highly insignificant when the leverage dummy is added indicates that the GJR dummy increases the goodness-of-fit of the model compared to the GARCH model. Thus the asymmetric element of financial times series is found to be highly significant and of great importance for the model specification in the whole period. Also the LB-Q(6) test support this finding.

In sum, the asymmetric properties of financial time series are of great importance and captured by the dummy variable in the GJR-GARCH model, which makes this model desired in the subsequent testing. We will in the following Test 3 apply the GJR-GARCH model with derivatives variables in rolling periods that include at least one upturn and one downturn to take advantage of the asymmetric dummy. The inclusion of two different periods ensures a meaningful interpretation of the leverage effect dummy, which in theory will be higher (in absolute terms) in downturns than in upturns due to the arrival of more negative information than in upturns. However, the leverage effect dummy is also found to be significant in isolated periods, which can be explained by fluctuations relative to the overall trend in these periods.

In isolated periods we will apply the GARCH model with derivatives variables. We chose to use the GARCH model in isolated periods for reasons. 1) The results from the GJR-GARCH model are biased in some isolated periods due to the rigidity of the estimation method and the model, and 2) Parsimony of the model is a desired feature (as discussed in the model selection section). The table below supports the significance and our use of the GARCH model in isolated periods. Here the LM tests for the GARCH substantially more insignificant for period 1 and 2, while the GJR-GARCH is just a little better in period 3,4 and 5 (but very close).

Table 4.2. Test value for GJR-GARCH vs. GARCH

LM Test values	Period 1 p-value	Period 2 p-value	Period 3 p-value	Period 4 p-value	Period 5 p-value
LM Test (GJR)	0.1060	0.3568	0.2826	0.1743	0.3633
LM Test	0.1559	0.5221	0.1570	0.1549	0.3537

4.1.2 Test 3 – results and comments

Test 3 is divided into two tests depending on whether we use the GARCH model with ARMA processes in isolated periods (a) or use the GJR-GARCH model with ARMA processes in rolling periods (b). The hypotheses tested are H_1, H_2 and H_4 where we test for the total effect of derivatives trading, the effect from different agents in the derivatives markets and various market conditions.

The GARCH model employed is: $\sigma_t^2 = \alpha_0 + \sum \alpha_1 \varepsilon_{t-1}^2 + \sum \beta_1 \sigma_{t-j}^2 + OI_{t-1} + VOL_{t-1}$: while the GJR-GARCH model takes the form: $\sigma_t^2 = \alpha_0 + \sum \alpha_1 \varepsilon_{t-1}^2 + \sum \beta_1 \sigma_{t-j}^2 + \gamma \varepsilon_{t-j}^2 I_{t-1} + OI_{t-1} + VOL_{t-1}$

Test number	Refered	Level	Instrument(s) used	Period	Econometric model	Effects tested on
Test 3A and 3B	H1 + H2 + H4	Index	All derivatives devided into OI and VOL variables	Every periods	ARMA-(GJR)-GARCH model	Total derivates trading Diffent agents Market condition

Technically the GARCH coefficients (β_0) are constructed from the lagged variances and can theoretically be interpreted as the effect of news arrived to the market participants before yesterday; that is volatility persistence. From test 3A (See Table 4.3.) we find persistence in volatility (although not indefinitely, which would imply a coefficient of 1) in all subperiods analyzed through significant GARCH coefficient that range between 0.84 in period 1 and 0.95 in period 4. We find that persistence in volatility seems to increase over time and peak in period 4, which include the last financial crisis following the subprime crisis. A minor decrease in the volatility persistence is observed in period 5, which could indicate the beginning of a more stable period on the Swedish financial market. The fact that the GARCH coefficients have increased and not substantially decreased compared to the GARCH model from test 1, after the inclusion of the trading activities variables indicates that the model do not capture all the GARCH effects in the sup-periods. News arrived to market participants before yesterday thus seems to have an increasingly effect in the volatility. This is supported by significant LM tests for autocorrelation in period 1, 3 and 4 that are found significant at a 5% level. Theoretically this has been interpreted as a low degree of market efficiency and a low effect of increased market information.[130]

The intercept α_0 is found to be significant only in the whole period. In subperiods we observe sign changing and insignificant α_0, which indicate that the unconditional variance has remained unchanged in sub-periods. In relation to our theoretical investigation, α_1 (often referred to as the ARCH effects in financial time series), can be interpreted as the impact of past news on the current volatility. Technically α_1 is constructed from the lagged error term, which means that a change in α_1 also can be interpreted as the effect from the difference between yesterdays expected return and realized return. This is more or less the same interpretation as with the effect from the information flow. For α_1 we find significant estimates and positive coefficients for the whole period and period 1 – 3, while we find insignificant estimates for the two last periods. We observe a general decreasing trend in the size of the ARCH parameter from 0.11 in period 1 to 0.048 in period 5, which indicates that the impact of past news on current volatility have decreased over the analyzed period. In the whole period the ARCH parameter is estimated to be 0.069 and significant. This value is higher than all the coefficients for the period interval from 2 through 5, and we can therefore conclude that the impact from the ARCH parameter in period 1 is relative high. The insignificant estimate for periods 4 – 5 indicates that past news do not have any significant effect on the spot volatility, which contradicts our prior expectations to the model

[130] Cox (1976); pp. 1.229 – 1.232.

and information theory. However, the insignificance may be explained by the inclusion of derivatives trading variables that may capture some of the influences from past information due to the linkages between the derivatives markets and mitigation of information.

Table 4.3. Test 3A results. ARMA-GARCH(1,1) + OI + VOL for separate Sub-periods

TEST 3A	Whole Period		Period 1		Period 2		Period 3		Period 4		Period 5	
	Estimates	P-STAT	Estimates	P-STAT	Estimates	P-STAT	Estimates	P-STAT	Estimates	P-STAT	Estimates	P-STAT
Intercept	0.094091	<.0001	0.152688	<.0001	-0.17134	0.0255	0.105691	<.0001	-0.18867	0.0661	0.141572	0.0492
ARCH 0	-0.12802	0.0033	-0.38738	0.0685	11,10112	0.4892	0.18819	0.2819	-66,5483	0.0438	-0.10267	0.9288
ARCH	0.069012	<.0001	0.116175	<.0001	0.067859	0.0038	0.058642	0.0011	0.034201	0.1929	0.048053	0.1608
GARCH	0.909052	<.0001	0.840474	<.0001	0.885428	<.0001	0.902335	<.0001	0.953231	<.0001	0.935595	<.0001
ρ 1 (OI)	-0.02939	<.0001	0.029705	0.3534	-0.00366	0.9785	-0.01326	0.2210	0.423982	0.0355	-0.01875	0.8176
ρ 2 (VOL)	0.045471	<.0001	0.008373	0.7871	-0.07985	0.4371	0.001268	0.9331	0.042452	0.8423	0.030682	0.6664
TEST LM	**4.93**	**0.0264**	**3.85**	**0.0498**	**0.40**	**0.5247**	**3.71**	**0.0541**	**3.50**	**0.0615**	**0.86**	**0.3527**
LB-Q (6) test	**11.06**	**0.0864**	**9.96**	**0.1262**	**0.78**	**0.9926**	**11.26**	**0.0807**	**3.28**	**0.7730**	**8.65**	**0.1945**

Furthermore, the volume and the open interest variables are found to be insignificant for all subperiods, which indicate that the volatility in the subperiods cannot be explained by these variables. However, the coefficients of the lagged volume variables are positive in all sub-periods, excluding period 2, which correspond to our findings in the theoretical section where we linked the trading volume and the volatility. Here an increased volatility was linked to the trading volume following an announcement that alters the cash flow substantially. In our framework of speculative and hedging activities this means that speculators destabilize the markets. The sign of the coefficients of the lagged open interest variable is ambiguous and changing. In upturn periods the coefficient seems to be positive, while negative in downturn periods, indicating a positive relation between hedging activities and the volatility in upturn markets and a negative relation in downturn markets. This finding contradicts both our prior expectations and the investigated financial theory where a stabilizing effect from hedging activities in general was predicted. Open Interest thus seem to have a positive effect on the underlying spot volatility (destabilizing), and we therefore accept hypothesis 4; that the underlying spot volatility is affected differently in upturn periods than in downturn periods. However, the sum of the coefficients for both trading activity variables is found to be unstable over time with no patterns, which suggest that the model do not fit the subperiods very well, while the model seems to fit more appropriately for the whole period where all the trading activities variables are found significant. Trading activities from hedgers is found to have a stabilizing effect on the volatility while speculators seem to destabilize the underlying spot volatility in general from test 3 and we therefore accept H_1 and H_2.

In test 3B we include the documented leverage effect variable and estimate in rolling periods. Here we find high persistence in the volatility and a significant leverage effect variable for all estimated periods. The sign of the coefficient of the leverage effect variable is negative for all periods, which indicate that negative news has a greater impact on volatility than positive news. We have thus documented the leverage effect in financial time series.

The unconditional variance α_0 is found to be insignificant for most of the periods, which implies that the unconditional variance has remained unchanged during the analyzed period. α_1 is found to decrease overtime while the persistence in volatility is found to increase and be significant (β_0) in all periods. The effect from arrival of information before yesterday thus seems to increase in the analyzed period. Also the open interest and the volume variables are found to be significant for most of the rolling periods. Period 1-3 is an exception to this finding and exhibit insignificant trading activity variables. This finding may suggest that the inclusion of period 3 may violate the assumption of the GJR-GARCH model. From the data selection section we concluded that period 3 is the longest estimated period consisting of a bull market. The unusual length and the scope of this upturn period may explain the insignificant results in this period. However, the subsequent period 1-4 is found to be significant for all variables. The results from test 3B can be found in the table below:

Table 4.4. Test 3B results. ARMA-GJR-GARCH(1,1,) + OI + VOL

TEST 3B	Whole Period		Period 1		Period 1 - 2		Period 1 - 3		Period 1 - 4	
	Estimates	P-STAT	Estimates	P-STAT	Estimates	P-STAT	Estimates	P-STAT	Estimates	P-STAT
Intercept	0.064323	0.0005	0.127551	0.0283	0.072773	0.0103	0.077928	<.0001	0.06087	0.0020
ARCH 0	-0.0753	0.0677	-0.515	0.1981	-0.43575	0.0279	0.027594	0.7026	-0.00484	0.9027
ARCH	0.111995	<.0001	0.169284	0.0246	0.152243	<.0001	0.121847	<.0001	0.120041	<.0001
GARCH	0.911128	<.0001	0.837996	0.0194	0.871895	<.0001	0.898076	<.0001	0.907321	<.0001
ϕ (GJR)	-0.09456	<.0001	-0.11825	0.0249	-0.12074	<.0001	-0.09825	<.0001	-0.10291	<.0001
ρ 1 (OI)	-0.02779	<.0001	0.016042	0.0190	0.046123	0.0151	-0.01575	0.1019	-0.01674	0.0155
ρ 2 (VOL)	0.039634	<.0001	0.03585	0.0199	-0.00533	0.7888	0.017609	0.2525	0.0213	0.0114
TEST LM	**0.58**	**0.4467**	**2.81**	**0.0935**	**3.71**	**0.0540**	**1.52**	**0.2175**	**0.93**	**0.3341**
LB-Q (6) test	**4.01**	**0.6749**	**9.43**	**0.1510**	**3.80**	**0.7032**	**4.02**	**0.6736**	**2.65**	**0.8519**

The sign of the coefficient of the volume variable is found to be positive and stable for all periods. Lagged trading volume is thus found to increase the volatility of the underlying spot market (Hence speculators are found to destabilize the market). The sign of the open interest coefficient is negative from the estimation of period 1-3 and onward, but positive prior this period and significant for all periods estimated. However, for the whole period we find highly significant trading activity variables. Both the LM test value and the Ljung-Box Q test are found to be highly insignificant, which means that the model is well-specified and that GARCH effects are captured appropriately. In addition, the LM test is most insignificant for the whole periods, which indicate that the model is best fitted for the whole period.

In sum, from test 3A and 3B we can conclude that derivatives trading do affect the underlying volatility when we measure in the whole period for both the GARCH and the GJR-GARCH model with open interest and volume variables. We thus accept out main hypotheses (H_1). We can from test 3B document the existence of the leverage effect, which has an increasing effect on the volatility of the underlying spot volatility. Also the relation between speculators trading activities (which were approximated to the Volume) and the volatility is found to be both significant and positive for the whole period, while the effect from hedgers are ambiguous to some extend. We therefore accept Hypothesis 2, that some agents in the derivatives market affect the volatility more than others. The results from the effect from hedgers is more ambiguous where we in upturn markets observe the coefficient of the open interest variables to be negative, which can be interpreted as a stabilizing effect on the volatility, while we in downturn periods find a negative relation. Thus we find that the effect from derivatives trading from both hedgers and speculators have a destabilizing effect on the volatility in bear markets where the coefficient of the leverage effect dummy also takes the highest absolute value. These findings support the acceptance of H_4, but due to the previously mentioned insignificance of the trading variables we have to reject H_4. From test 3B we find similar results for the overall period, but find no evidence for neither a decreasing nor an increasing effect from trading activities in derivatives on the underlying spot volatility.

4.1.3 Test 4 - results and comments

In test 4 we extended the model to include variables of expected and unexpected trading activities in derivatives from different agents in the market.

Test number	Refered	Level	Instrument(s) used	Period	Econometric model	Effects tested on
Test 4	H1 + H2 + H4	Index	All derivatives (ExpectedOI + ExpectedVOL +	Every periods	ARMA-(GJR)-GARCH model	Total derivates trading Diffent agents Shocks from agents

Separating these variables into expected and unexpected activities makes it possible for us to test the effect from shocks from different agents in the derivatives market.

We used the following GJR-GARCH model due to the significance of the leverage effect variable in the preceding test

$\sigma_t^2 = \alpha_0 + \sum \alpha_1 \varepsilon_{t-1}^2 + \sum \beta_1 \sigma_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1} + \delta_1 UNEXVOL_t + \delta_2 EXVOL_t + \delta_3 UNEXOI_t + \delta_4 EXOI_t.$,

moreover, for subperiods the test was only conducted for test 3A, while we in the following do estimation in rolling periods due the characteristics of the model and the findings from test 3A. The estimation results can be found in Table 4.5. below.

Table 4.5. Test 4 results. ARMA-GJR-GARCH(1,1,) + uexpOI + expOI + unexpVOL + expVOL

TEST 4	Whole Period		Period 1		Period 1 - 2		Period 1 - 3		Period 1 - 4	
	Estimates	P-STAT	Estimates	P-STAT	Estimates	P-STAT	Estimates	P-STAT	Estimates	P-STAT
Intercept	0.06987	0.0006	0.122704	<.0001	0.073979	0.0115	0.077611	<.0001	0.054085	0.0051
ARCH 0	0.763276	<.0001	0.161061	0.2791	-0.35638	0.2722	-0.07214	0.5669	-0.12708	0.2114
ARCH	0.125975	<.0001	0.14531	0.5141	0.158547	<.0001	0.124753	<.0001	0.133233	<.0001
GARCH	0.889761	<.0001	0.854146	<.0001	0.866363	<.0001	0.896355	<.0001	0.905385	<.0001
ϕ (GJR)	-0.0923	<.0001	-0.08421	<.0001	-0.12545	<.0001	-0.10082	<.0001	-0.1131	<.0001
δ 1 (uexpOI)	-0.86244	<.0001	-0.52654	0.0058	-0.23606	0.3685	-0.02236	0.9297	-0.02262	0.9209
δ 2 (expOI)	0.010441	0.2798	0.05516	0.0094	0.056038	0.0757	-0.01562	0.1156	-0.02123	0.0208
δ 3 (unexpVOL)	0.501158	<.0001	0.401418	0.0218	0.08143	0.5575	-0.0317	0.5937	-0.01803	0.7396
δ 4 (expVOL)	-0.07338	<.0001	-0.07062	<.0001	-0.02279	0.5190	0.026137	0.1428	0.037089	0.0265
TEST LM	**0.12**	**0.7298**	**2.32**	**0.1274**	**3.68**	**0.0552**	**1.53**	**0.2157**	**0.61**	**0.4337**
LB-Q (6) test	**5.09**	**0.5318**	**7.34**	**0.2910**	**4.62**	**0.5929**	**4.02**	**0.6744**	**3.09**	**0.7970**

We find insignificant α_0 (ARCH0) for every rolling period except for the whole period, which implies unchanged unconditional volatility in the analyzed period. The effect from past information to the market participants (α_1) on volatility is found to be positive and significant for all the analyzed periods. The change in the size of the coefficient from period 1 to period 2 is positive, while the change in the coefficient from period 1-2 to period 1-3 is negative. In general we observe a larger effect from past information in periods dominated by downturn periods, while a negative change can be observed in rolling periods dominated by upturns. This indicates that the impact of yesterday's news arrival has greater impact in downturns than upturns (regardless of whether the information reviled is positive or negative). Also the leverage effect dummy is found significant with negative coefficient signs, which support its existence; that is negative news in particular affect the volatility more than positive news. The persistence in volatility exhibit an increasing trend but remain relatively stable over time, which suggest that shocks from information before yesterday tend to decay slowly. The conditional volatility ($\beta_1 + \alpha_1$) change from one period to another where decreases are observed in periods dominated by upturns while increases are observed in periods dominated by downturns. The most of the variation in the conditional volatility is therefore due to the variation in α_1, which suggest that the conditional volatility changes in accordance with yesterday's news, while the effect from the persistence in volatility caused by news arrival before yesterday seems stable.

The estimates for the trading activity variables are insignificant for the rolling periods (excluding period 1), which suggest that trading activities in derivatives in sub-periods (H_4) cannot be used as variables for explaining the underlying spot volatility when we split the data into expected and unexpected trading variables. Nevertheless, a general trend of the signs of the trading variables can be observed, where negative coefficients dominate upturn markets and positive coefficients dominate downturns markets (regardless of the insignificant estimates). Period 1 is an exception to this where both expected and unexpected open interest and expected volume are significant, while unexpected volume is insignificant. The sign of the coefficient of the expected open interest is positive in period 1, which align with our prior expectations and supports the previous literature, where hedgers trading activities in derivatives are found to stabilize the underlying market. We will in the following only comment upon our findings for the whole period due to the insignificance of the trading activity variables in sub-periods.

For the whole period we find significant trading variable estimates except for the expected open interest, which is insignificant up to a 30% confidence level. Unexpected open interest is highly significant and negative. The sum of expected and unexpected open interest coefficients are negative, which indicates that unexpected trading activities from hedgers has a stabilizing effect on the underlying spot volatility. The negative and insignificant coefficient for the expected open interest is in contrast to previous findings.[131] The sum of the expected and unexpected open interest also suggest that an enhanced market depth, which expected and unexpected open interest can be approximated to due to its definition (the number of traders in the beginning of the day), may have negative effect on the underlying spot volatility. Theoretically this can be interpreted as a negative relation between the capital associated with a market and the underlying volatility. The volume coefficients are both found to be highly significant. The size of the expected volume coefficient is negative, while the sign for the unexpected volume coefficient is positive. The sum of the two coefficients is positive, which suggest a positive relation between trading volume and volatility (H_1). This is only found for unexpected shocks, which indicate that unexpected trading activities from speculators destabilize the underlying spot market. In a theoretical perspective this means that more information is revealed from unexpected shocks of volatility that expected volatility. The coefficient of the expected volume is negative, which contradict the theoretical

[131] Bassembinder & Seguin (2003), Pati (2008)

relation between volume and price volatility investigated earlier. The coefficient is only significant for the whole period and has a very little absolute size of 0.07338. The negative relation may suggest that the underlying spot volatility is not driven by the size of the expected trading volume. The expected trading volume could theoretically already have been incorporated in underlying spot price, which should reflect a lower liquidity premium.[132] This argument also supports the efficient market hypothesis in its semi-strong form. For the unexpected trading volume we only find positive and significant coefficients for the whole period. The coefficient is 0.501158, which is almost seven times larger than for the negative effect from the expected trading volume, and suggests that shocks from speculators trading activities are very affective on the underlying volatility than expected volume. The sum of the expected and unexpected coefficient is 0.4277 and we thus find a positive relation between speculators activities and the volatility of the underlying index. This aligns with our prior expectations and the financial theory about the Mixture of Distribution Hypothesis (MDH). The MDH predicts that price volatility and volume is driven by the same information, which creates leptokurtosis in the return distribution. We both identify leptokurtosis in the return data for the daily index prices and find evidence that price changes are driven by the same information as lagged volume. Hence we can conclude that volatility is conditioned on volume. In addition, the sum of unexpected volume and unexpected open interest is negative for the whole period (-0.3612). This suggests a total decreasing effect from unexpected shocks from derivatives trading activities on the underlying volatility, where the shocks from hedgers dominate those from speculators. This finding contradict the dispersion of believes hypothesis, that predict that speculators create excess volatility and are dominant in the market when important news are announced. Hedgers are in contrast risk adverse to excess return, which reinforce the dominant position of speculators. A direct consequence of this mechanism and behaviour of the agents in the market is volatility clustering. We document volatility clustering in the return of the index prices and that shocks from speculators trading activities in index derivatives affect the underlying volatility of the index, but also that the effect from unexpected trading activities from hedgers dominate that of speculators. Thus our results supports the theory about the MDH and contradict to some extend the dispersion of believes hypothesis. The two information hypotheses are different in their assumptions regarding the

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[132] French & Roll (1986). pp. 7 – 8.

informed versus uninformed traders. The MDH does not distinct between the two types of market participants while the dispersion of believes hypothesis does.

Finally, both the LM and the LB-Q(6) tests are highly insignificant, which are clear signs of an appropriate goodness-of-fit for the whole period and no significant ARCH effects left. Thus the model captures the statistical properties of financial time series in a satisfactory manner. The insignificant derivative trading variables for all the sub-periods suggest the model is most useful on very long data series in predicting the conditional volatility from derivatives trading activities.

4.1.4 Test 5 - results and comments

In test 5 we included variables for different types of derivatives to test whether trading activities in some derivatives have a larger effect on the underlying volatility than others (H2). The test was only conducted on the whole period due to our findings for the whole period and some preliminary test in subperiods where the trading derivatives were found highly insignificant. We only distinguish between trading activities in options and futures, but include both volume and open interest variables.

Test number	Refered	Level	Instrument(s) used	Period	Econometric model	Effects tested on
Test 5	H1 + H2 + H3	Index	All derivatives (optionOI+optionVOL + futuresOI +	The whole period	ARMA-(GJR)-GARCH model	Total derivates trading Diffent agents Types of derivatives

From Table 4.6. it can be observed that we find similar results for the GJR-GARCH variables as for the previous tests. The leverage effect is present and significant; the unconditional variance (ARCH0) is found insignificant, which indicate that it will remain constant over time; the effect from yesterday’s information on the volatility (ARCH1) is found significant and around 0.1, while the impact from the information prior yesterday remains relatively high around 0.9, which indicate high persistence in the volatility.

Table 4.6. Test 5 results. ARMA-GJR-GARCH(1,1,) + optOI + futOI + optVOL + futVOL

TEST 5	Whole Period	
	Estimates	P-STAT
Intercept	0.064575	0.0007
ARCH 0	0.156135	0.1171
ARCH 1	0.118544	<.0001
GARCH	0.904759	<.0001
ϕ (GJR)	-0.10286	<.0001
δ 1 (futOI)	-0.00841	0.5706
δ 2 (futVOL)	0.022744	0.0872
δ 3 (optOI)	-0.00866	0.5946
δ 4 (optVOL)	-0.01485	0.4966
TEST LM	**0.64**	**0.4247**
LB-Q (6) test	**3.47**	**0.7483**

Conversely, all derivatives variables are found insignificant which indicate that separation into types of derivatives does not explain the volatility pattern in the underlying index. The test results of the GJR-GARCH model from Test 2 are very close to the results in Test 5 and we can thus conclude that inclusion of futures and option variables in this relation is irrelevant (regardless of the more insignificant LM and LB-Q(6) tests). However, the insignificance may be explained by a low liquidity in index options compared to index futures, and for the index futures volume we observe positive coefficients, which correspond to the found relation between volume and volatility from previously tests. We therefore reject our stated hypothesis about the effect from different types of derivatives (H_3).

The following tests (6 – 8) are all conducted on asset level from where we will draw general conclusions upon. We will in the end of the analysis part sum all the tests up in relation to our stated hypotheses in a part conclusion where we also distinguish between index and asset results.

4.1.5 Test 6 - results and comments

In test 6 we used the basic GJR-GARCH model to find out whether the later included derivatives trading activity variables would explain the volatility changes in the underlying volatility better than a model without.

Test number	Refered	Level	Instrument(s) used	Period	Econometric model	Effects tested on
Test 6	H1 + H2	Asset	Return series	The whole period	GJR-GARCH model	GARCH(1,1) processes in the return series

Table 4.7. Test 6 results. (ARMA(p,q))-GJR-GARCH(1,1)

TEST 6	AR	P value	MA	P value	Intercept	P value	arch0	P value	arch1	P value	garch1	P value	phi	P value	LM-TEST	P value	LB-Q(6)	P value
ABB LTD	-	-	-0.01898	0.3837	0.099483	0.0115	0.122773	<.0001	0.11801	<.0001	0.827601	<.0001	-0.05733	0.0045	1.88	0.1706	1.21	0.9764
ASTRAZENECA	-	-	-	-	-0.0131	0.6574	0.024372	0.0343	0.046762	0.0004	0.934143	<.0001	-0.02549	0.0395	1.71	0.1903	1.24	0.9747
ATLAS COPCO A	-	-	-	-	0.036907	0.2912	0.038421	0.0026	0.070223	<.0001	0.944122	<.0001	-0.0622	<.0001	1.96	0.1619	3.80	0.7040
AUTOLIV SDB	-	-	-0.04199	0.0169	-0.01618	0.5777	0.045386	0.0031	0.056225	<.0001	0.923263	<.0001	-0.03988	0.0006	0.53	0.4681	1.43	0.9639
ELECTROLUX B	-	-	-	-	0.026869	0.3278	0.013512	0.0256	0.037495	<.0001	0.956607	<.0001	-0.02572	<.0001	8.59	0.0034	8.68	0.1924
ERICSSON B	-	-	-0.01333	0.4229	0.085481	0.0132	0.019182	0.0103	0.040053	<.0001	0.948356	<.0001	-0.01487	0.0299	0.97	0.3246	0.78	0.9927
HENNES & MAURITZ B	0.747703	<.0001	0.741303	<.0001	0.060565	0.0059	0.044668	0.0067	0.064581	<.0001	0.910783	<.0001	-0.04117	0.0005	3.56	0.0592	2.09	0.9109
HOLMEN B	-	-	-	-	0.022059	0.4944	0.024974	0.0925	0.052046	0.0407	0.914341	<.0001	-0.00928	0.6638	1.29	0.2555	0.28	0.9996
INVESTOR B	-	-	-	-	0.047742	0.0426	0.072684	<.0001	0.115672	<.0001	0.875664	<.0001	-0.08501	<.0001	1.14	0.2867	1.72	0.9437
LUNDIN PETROLEUM	-	-	-	-	-0.01157	0.8855	0.185186	0.0084	0.126316	<.0001	0.839645	<.0001	-0.06391	0.0241	0.12	0.7257	9.63	0.1412
NOKIA CORPORATION	-	-	-	-	0.098889	0.0046	0.007191	0.2028	0.015297	0.0039	0.966995	<.0001	0.007825	0.1507	2.30	0.1295	0.19	0.9999
SANDVIK	-	-	-	-	0.053138	0.0556	0.022313	0.0083	0.047246	<.0001	0.94411	<.0001	-0.01747	0.0355	2.36	0.1245	6.72	0.3477
SCA B	-	-	-	-	0.002469	0.9171	0.058353	0.0016	0.101275	<.0001	0.864068	<.0001	-0.04631	0.0018	0.54	0.4636	6.26	0.3951
SEB A	-	-	-	-	0.030799	0.2500	0.04703	0.0002	0.089707	<.0001	0.911543	<.0001	-0.0634	<.0001	1.89	0.1691	3.75	0.7103
SKANSKA B	-	-	-	-	0.046789	0.0678	0.085717	<.0001	0.097171	<.0001	0.869187	<.0001	-0.06288	<.0001	2.31	0.1289	2.57	0.8608
SKF B	-	-	-	-	0.042512	0.1923	0.035022	0.1579	0.050675	0.0050	0.94753	<.0001	-0.04086	0.0024	0.55	0.4590	10.18	0.1173
STORA A	-	-	-0.09368	0.0040	-0.01959	0.7635	0.015735	0.3000	0.068549	<.0001	0.94855	<.0001	-0.04991	0.0061	0.55	0.4578	2.65	0.8509
STORA ENSO R	-	-	0.000378	0.0709	0.000378	0.9914	0.013043	0.0421	0.035517	<.0001	0.957248	<.0001	-0.01303	0.1375	1.31	0.2525	2.73	0.8420
SV. HANDELSBANKEN A	0.755153	<.0001	0.805905	<.0001	0.043572	0.0654	0.031974	0.0024	0.095247	<.0001	0.88869	<.0001	-0.04907	0.0090	1.02	0.3121	2.68	0.8478
TELE2 A	-	-	-	-	0.043403	0.1932	0.075778	0.0008	0.074707	<.0001	0.907667	<.0001	-0.04893	<.0001	3.21	0.0732	2.53	0.8656
TELIASONERA	-	-	-	-	0.05493	0.1079	0.011909	0.1632	0.016748	0.0048	0.970619	<.0001	-0.0101	0.0819	3.69	0.0547	1.28	0.9725
TRELLEBORG B	0.019785	0.2127	-	-	-0.02354	0.3845	0.059431	<.0001	0.063453	<.0001	0.909815	<.0001	-0.03699	<.0001	3.76	0.0524	5.16	0.5240
VOLVO B	-	-	-	-	0.032496	0.2412	0.058546	0.0007	0.069028	<.0001	0.909152	<.0001	-0.03394	0.0022	2.52	0.1121	1.90	0.9283

From test 6 we find both ARCH coefficients estimates to be significant and positive (Table 4.7. on the previous page). Exceptions are Holmen, Nokia, SKF, Stora and TeliaSonera, where we find insignificant α_0. The effect from yesterday's information on the underlying volatility of today (α_1) is significant for all companies and positive in the range from 0.0153 to 0.1263, and with an average of 0.0675. We thus find that the spot price volatility of some companies are more affected by yesterday's news, while others are more affected by the long term effect from news (β_1). The companies with the lowest effect from yesterday's news also exhibit the highest effect from the news arrived to the market before yesterday (higher degree of volatility persistence). We thus find a relation between yesterday's news and information arrived before yesterday. In general we can conclude that the found persistence in the volatility is high

An important finding is the significant coefficient for leverage effect dummy for most of the companies. Only four exceptions are found from where three also exhibited insignificant α_0. We will therefore continue to include the leverage effect dummy in the subsequent tests on asset level.

Finally, both the LM test and the LB-Q(6) test are found insignificant for the majority of the companies which suggest that the GJR-GARCH model is well-specified for the analyzed data to explain most of today's volatility and that no ARCH effects remain in the data.

4.1.6 Test 7 - results and comments

In test 7 we use the ARMA(p,q)- GJR-GARCH(1,1) model with open interest and volume variables to test for the effect from trading activities from different traders in the whole period.

Test number	Refered	Level	Instrument(s) used	Period	Econometric model	Effects tested on
Test 7	H1 + H2	Asset	All derivatives devided into OI and VOL variables	The whole period	ARMA-(GJR)-GARCH model	Total derivates trading Diffent agents

The results (See Table 4.8) for the ARCH and GARCH coefficients are similar to those of test 6 and significant. Also the coefficient estimates for the leverage effect dummy is found significant for the majority of the companies (exceptions are the same as in test 6). We find less supporting answers when we look at the derivatives trading variables. The open interest variable is only found to be significant in 6 out of the 23 analyzed companies, which makes a general conclusion about the effect from hedgers trading activities in derivatives difficult.

Table 4.8. Test 7 results. ARMA(p,q)-GJR-GARCH(1,1,) + OI + VOL

TEST 7	AR	P value	MA	P value	Intercept	P value	arch0	P value	arch1	P value	garch1	P value	phi (φ)	P value	ρ1-OI	P value	ρ2-VOL	P value	LM-TEST	P value	LB-Q(6)	P value
ABB LTD	-	-	-0.01613	0.4728	0.076936	0.0421	0.320398	0.1828	0.144747	<.0001	0.785918	<.0001	-0.07738	0.0011	-0.11023	<.0001	0.139793	<.0001	2.82	0.0929	0.86	0.9904
ASTRAZENECA	-	-	-	-	-0.03076	0.3170	0.46493	0.2921	0.136986	0.0181	0.815849	<.0001	-0.09392	0.0371	-0.00914	0.8190	-0.02945	0.1526	1.52	0.2181	3.94	0.6848
ATLAS COPCO A	-	-	-	-	0.037135	0.2975	0.066986	0.2908	0.071185	<.0001	0.94282	<.0001	-0.06213	<.0001	0.004569	0.6897	-0.01043	0.4228	1.67	0.1961	3.82	0.7009
AUTOLIV SDB	-	-	-0.01746	0.5476	-0.0431	0.0144	0.196227	0.0539	0.059789	<.0001	0.914696	<.0001	-0.0429	0.0003	-0.02831	0.0725	0.021093	0.0726	0.52	0.4709	1.58	0.9541
ELECTROLUX B	-	-	-	-	0.026994	0.3156	0.05888	0.0926	0.036038	<.0001	0.959081	<.0001	-0.02551	<.0001	0.004804	0.3999	-0.01286	0.1220	7.16	0.0074	7.20	0.3028
ERICSSON B	-	-	0.082851	0.0154	-0.01317	0.4494	0.05904	0.1699	0.038541	<.0001	0.951899	<.0001	-0.01755	0.0102	-0.01659	0.0170	0.017114	0.0628	1.03	0.3094	0.70	0.9945
HENNES & MAURITZ B	0.693302	<.0001	0.685057	<.0001	0.058242	0.0090	0.223382	0.0053	0.072052	<.0001	0.897476	<.0001	-0.05209	<.0001	-0.04257	0.0030	0.039077	0.0074	3.47	0.0626	2.30	0.8902
HOLMEN B	-	-	-	-	0.022059	0.5475	-0.04976	0.9292	0.05319	0.3699	0.910974	<.0001	-0.00998	0.8126	0.007495	0.9380	0.002124	0.9718	1.22	0.2695	0.29	0.9995
INVESTOR B	-	-	-	-	0.048589	0.0387	0.114907	0.2817	0.112868	<.0001	0.881518	<.0001	-0.08561	<.0001	-0.01584	0.1798	0.016376	0.0583	1.04	0.3071	1.83	0.9346
LUNDIN PETROLEUM	-	-	-	-	-0.01068	0.8664	0.191337	0.6579	0.126832	<.0001	0.839211	<.0001	-0.06418	0.0241	0.000644	0.9845	-0.00156	0.9710	0.12	0.7242	9.64	0.1408
NOKIA CORPORATION	-	-	-	-	0.099194	0.0048	0.018766	0.8316	0.01404	0.0219	0.969038	<.0001	0.008531	0.1833	0.001487	0.9079	-0.00359	0.6671	2.52	0.1125	0.18	0.9999
SANDVIK	-	-	-	-	0.052853	0.0533	0.048384	0.2073	0.045428	<.0001	0.946875	<.0001	-0.01932	0.0200	-0.01017	0.2432	0.011321	0.2622	2.15	0.1424	7.35	0.2898
SCA B	-	-	-	-	0.001868	0.9457	0.417753	0.0005	0.100598	<.0001	0.855459	<.0001	-0.04666	0.0020	-0.02266	0.0663	-0.01375	0.1983	0.47	0.4941	5.24	0.5129
SEB A	-	-	-	-	0.031122	0.2293	0.132849	0.3273	0.089912	<.0001	0.908066	<.0001	-0.06529	<.0001	-0.01974	0.1761	0.019319	0.0561	1.92	0.1663	4.22	0.6472
SKANSKA B	-	-	-	-	0.046221	0.0659	0.059638	0.4867	0.099524	<.0001	0.867157	<.0001	-0.06511	<.0001	-0.0032	0.7782	0.008912	0.4736	2.32	0.1276	2.59	0.8577
SKF B	-	-	-	-	0.042838	0.1947	0.116211	0.4526	0.0597	0.0213	0.935721	<.0001	-0.04685	0.0123	-0.00504	0.8660	-0.00283	0.9188	0.50	0.4782	8.62	0.1964
STORA A	-	-	-0.09255	0.0042	-0.01621	0.8010	-0.19004	0.0505	0.061091	<.0001	0.954782	<.0001	-0.05216	0.0027	0.00589	0.6901	0.021967	0.1797	0.97	0.3236	2.57	0.8602
STORA ENSO R	-	-	-0.03549	0.0614	0.001533	0.9894	0.166691	0.0977	0.035888	0.0025	0.957456	<.0001	-0.01627	0.2037	-0.02623	0.0132	0.017862	0.0584	1.40	0.2370	3.35	0.7643
SV. HANDELSBANKEN A	0.720743	<.0001	0.774383	<.0001	0.042751	0.0740	-0.24831	0.0481	0.100225	<.0001	0.877937	<.0001	-0.05324	0.0074	0.031829	0.0524	-0.0085	0.4582	0.86	0.3540	2.82	0.8317
TELE2 A	-	-	-	-	0.041519	0.2088	0.498356	0.0026	0.078864	<.0001	0.900055	<.0001	-0.05783	<.0001	-0.05408	0.0060	0.024934	0.1590	3.29	0.0697	2.96	0.8138
TELIASONERA	-	-	-	-	0.0547	0.1056	-0.10763	0.1191	0.017	0.0072	0.967939	<.0001	-0.01062	0.0871	0.015262	0.1310	-0.00754	0.3702	3.91	0.0481	1.49	0.9602
TRELLEBORG B	0.024962	0.1277	-	-	-0.03726	0.1743	0.223422	0.1117	0.126497	<.0001	0.840919	<.0001	-0.08061	0.0002	-0.02622	0.1724	0.02294	0.1539	5.33	0.0210	10.44	0.1074
VOLVO B	-	-	-	-	0.044544	0.1341	0.0424	0.7187	0.131912	<.0001	0.8847	<.0001	-0.085	<.0001	-0.01505	0.3269	0.03064	0.0822	2.26	0.1327	2.14	0.9061

Also the effect from the trading volume is found insignificant for the majority of the companies (21 out of 23) and we thus have to reject the Hypotheses 1 and 2 on the asset level from this model. However, even though the majority of the coefficient estimates are found insignificant we see a trend towards negative coefficients (14 out of 23) for the open interest variables and positive for the volume variables (14 out of 23), but with no relation between those with negative coefficients for open interest and those with positive coefficients for the volume variable.

4.1.7 Test 8 - results and comments

In test 8 we employ the ARMA-GJR-GARCH model with derivatives trading variables for expected and unexpected open interest and expected and unexpected volume for the whole period.

Test number	Refered	Level	Instrument(s) used	Period	Econometric model	Effects tested on
Test 8	H0 + H1 + H3	Asset	All derivatives (ExpectedOI + ExpectedVOL + UnexpectedOI + UnexpectedVOL)	The whole period	ARMA-(GJR)-GARCH model	Total derivates trading Diffent agents Shocks from agents

From the Table 4.9. it can be seen that some of our results have turned out to be biased. This biasness is due to problems of convergence a relatively high number of iterations in the estimation procedure in the statistical estimation program used (SAS). Nevertheless, the program still produce estimates for all the coefficients but fails to find the statistical significance of the coefficient estimates. We will use the coefficients from the biased results to draw conclusions about the effect on volatility from the sign of the coefficient, but do not count them as significant in the following (The corresponding ARMA coefficients can be found in the subsequent table 4.10).

Table 4.9. Test 8 results. (ARMA-)GJR-GARCH(1,1)+unexoi+exoi+unexvol+exvol

TEST 8	Intercept	P value	arch0	P value	arch1	P value	garch1	P value	phi (φ)	P value	unexpOI	P value	expOI	P value	unexpVOL	P value	expVOL	P value	LM-TEST	P value	LB-Q(6)	P value
ABB LTD	0.048721	0.2089	0.925376	<.0001	0.12422	<.0001	0.821023	<.0001	-0.06389	0.0033	-0.37076	0.0847	-0.02751	0.0750	0.403927	<.0001	-0.05377	0.0357	3.47	0.0624	0.77	0.9929
ASTRAZENECA	-0.02678	0.4447	0.100603	0.9427	0.154717	0.0271	0.655612	0.0067	-0.0476	0.2103	-0.39457	0.5541	0.010179	0.8954	0.30236	0.0174	0.010124	0.9485	0.87	0.3523	3.56	0.7366
ATLAS COPCO A	0.03612	0.3073	0.373356	<.0001	0.066394	<.0001	0.947613	<.0001	-0.06237	<.0001	0.066158	0.5796	-0.00544	0.6790	0.217936	<.0001	-0.03801	0.0254	2.12	0.1454	3.45	0.7512
AUTOLIV SDB	-0.02556	0.3680	0.252441	<.0001	0.031704	0.0003	0.95573	<.0001	-0.02186	0.0031	-0.39141	<.0001	-0.00218	0.8184	0.217681	<.0001	-0.02869	0.0011	9.22	0.0024	3.88	0.6928
ELECTROLUX B	0.036955	Biased	0.048389	Biased	0.093685	Biased	0.849594	Biased	-0.10794	Biased	0.096938	Biased	0.029609	Biased	0.127963	Biased	0.04106	Biased	3.30	0.0693	3.66	0.7220
ERICSSON B	0.07756	0.0212	0.3576	<.0001	0.035886	<.0001	0.953616	<.0001	-0.01527	0.0134	0.1908	0.5157	-0.00825	0.2196	0.370978	<.0001	-0.0196	0.0360	6.17	0.0130	1.40	0.9659
HENNES & MAURITZ B	0.022688	Biased	0.438157	Biased	0.076291	Biased	0.89393	Biased	-0.05805	Biased	-0.06844	Biased	-0.04169	Biased	0.298663	Biased	0.014593	Biased	1.97	0.1604	2.12	0.9081
HOLMEN B	0.005709	Biased	0.101966	Biased	0.103703	Biased	0.845607	Biased	-0.0906	Biased	0.080682	Biased	0.001292	Biased	0.095828	Biased	0.010467	Biased	1.03	0.3099	0.51	0.9977
INVESTOR B	0.036892	0.1398	0.292217	0.0841	0.116073	<.0001	0.884963	<.0001	-0.09436	<.0001	-0.22484	0.0416	0.003534	0.8398	0.16829	<.0001	-0.03438	0.0050	0.82	0.3662	2.18	0.9024
LUNDIN PETROLEUM	-0.04905	0.4562	2.598.084	<.0001	0.128546	<.0001	0.853806	<.0001	-0.0853	0.0036	-0.71471	0.1388	-0.13308	0.0372	0.6665	<.0001	-0.10829	0.1508	1.33	0.2493	7.99	0.2385
NOKIA CORPORATION	0.079838	0.0214	0.292451	0.0002	0.014697	0.0319	0.96462	<.0001	0.010674	0.0861	-0.65757	0.0095	0.011024	0.2724	0.381907	<.0001	-0.04694	<.0001	1.41	0.2351	0.57	0.9969
SANDVIK	0.036467	0.1788	0.16904	0.0003	0.047074	<.0001	0.947562	<.0001	-0.0244	0.0047	-0.37981	0.0047	-0.00593	0.5374	0.125529	<.0001	-0.0102	0.4194	2.17	0.1408	6.39	0.3807
SCA B	-0.00518	Biased	0.914499	Biased	0.108425	Biased	0.846411	Biased	-0.06998	Biased	-0.17812	Biased	0.03129	Biased	0.217508	Biased	-0.15331	Biased	0.66	0.4153	4.66	0.5887
SEB A	0.027956	0.2868	0.27026	0.0877	0.090277	<.0001	0.904561	<.0001	-0.066	<.0001	-0.2284	0.1124	-0.01543	0.3096	0.12429	<.0001	-0.00404	0.7967	1.28	0.2583	1.89	0.9297
SKANSKA B	0.053192	0.0322	0.770936	<.0001	0.103329	<.0001	0.864615	<.0001	-0.07511	<.0001	-0.18291	0.0023	0.011349	0.3523	0.203386	<.0001	-0.11587	<.0001	0.92	0.3378	2.38	0.8818
SKF B	0.014746	0.6938	0.717619	<.0001	0.046549	0.0005	0.952702	<.0001	-0.03959	0.0002	-0.37496	0.0011	0.014437	0.1486	0.282456	<.0001	-0.12131	<.0001	0.09	0.7637	7.32	0.2924
STORA A	-0.03849	0.5397	13,282	<.0001	0.053864	<.0001	0.963552	<.0001	-0.04798	0.0020	-0.16282	0.3443	0.008845	0.4416	0.376355	<.0001	-0.19027	<.0001	0.36	0.5463	3.39	0.7588
STORA ENSO R	-0.0047	0.9071	0.701399	<.0001	0.03214	<.0001	0.964126	<.0001	-0.01728	0.0327	-0.28822	<.0001	0.010278	0.3524	0.182722	<.0001	-0.11418	<.0001	14.26	0.0002	3.48	0.7463
SV. HANDELSBANKEN A	0.036965	0.1323	0.116211	0.5209	0.105596	<.0001	0.873565	<.0001	-0.05886	0.0050	-0.02317	0.7840	0.024662	0.2664	0.053758	0.0146	-0.04453	0.0878	0.93	0.3343	3.21	0.7818
TELE2 A	0.006582	0.8487	1.509.924	<.0001	0.093473	<.0001	0.886691	<.0001	-0.06953	<.0001	-0.6247	0.0081	-0.03374	0.0562	0.394994	<.0001	-0.13044	<.0001	3.03	0.0820	2.21	0.8994
TELIASONERA	0.005937	Biased	-0.01266	Biased	0.096954	Biased	0.836759	Biased	-0.06975	Biased	-0.3307	Biased	-0.00011	Biased	0.140875	Biased	0.016523	Biased	4.10	0.0429	2.25	0.8954
TRELLEBORG B	-0.06118	Biased	0.048981	Biased	0.102637	Biased	0.849959	Biased	-0.08715	Biased	0.417867	Biased	0.012163	Biased	0.126911	Biased	-0.001	Biased	6.76	0.0093	13.12	0.0412
VOLVO B	-0.00046	Biased	0.072343	Biased	0.109627	Biased	0.848607	Biased	-0.06643	Biased	0.109801	Biased	0.002278	Biased	0.338329	Biased	0.008018	Biased	2.79	0.0950	4.24	0.6447

Our ARCH1 and GARCH coefficients are found to be significant for most of the companies and exhibit stationarity. The sum of the ARCH1 and the GARCH coefficients show evidence of a decreasing trend compared to the GJR-GARCH model without derivatives variables (Test 6 versus Test 8). This may indicate that the inclusion of the derivatives variables reduces the persistence in the volatility. In general the results from Test 8 are similar to those of Test 7 and we can thus draw a similar conclusion; that the general GJR-GARCH model captures most of the ARCH effects in the asset returns and that the spot volatility primary is affected by both yesterday's information flow and the information arrived to the market before yesterday. The unexpected open interest estimates are found significant in 9 out of 23 companies, which is a substantial improvement compared to the open interest variable in Test 7. The general trend is negative coefficients (17 out of 23), which we interpret as trading shocks from hedgers stabilize the underlying spot price of the asset. Out of the 17 companies with negative coefficients for the expected open interest we find that 8 companies also have negative coefficients for unexpected open interest. These results are consistent with previous findings[133] and have been explained by a positive relation between the market depth and mitigation of volatility.

Table 4.10. Autoregressive and Moving Average processes in Test 8

TEST 8	AR1	P-value	MA1	P-value	MA2	P-value	MA3	P-value
ABB LTD	-	-	-0.01182	0.6253	-	-	-	-
AUTOLIV SDB	-	-	-0.03415	0.0513	-	-	-	-
Electrolux	-	-	-0.0153	Biased	0.051222	Biased	0.054479	Biased
ERICSSON B	-	-	-0.00615	0.7179	-	-	-	-
HENNES & MAURITZ B	0.706978	Biased	0.698715	Biased	0.05056	Biased	-	-
SEB	-	-	0.009602	0.5711	0.034886	0.0350	0.063914	0.0002
STORA A	-	-	-0.08163	0.0147	-	-	-	-
STORA ENSO R	-	-	-0.02738	0.1534	-	-	-	-
SV. HANDELSBANKEN A	0.66698	0.0002	0.725776	<.0001	-	-	-	-
TRELLEBORG B	0.030281	Biased	-	-	-	-	-	-

The most significant results from the derivatives trading variables are the coefficients from the unexpected volume where all the estimates are found significant, except for the unbiased estimators (16 out of 23). All the coefficients are positive and range between 0.0538 and 0.6665, which is substantially larger than all other trading variables in absolute terms. This indicates that

[133] Bassembinder & Seguin (1993) & Pati (2008)

the unexpected variable affects the underlying spot volatility the most, and that shocks from speculators destabilize the spot price. The highly significant results relative to the rest of the trading derivatives support this conclusion and align with the information hypothesis about the effect from noise trader, where these agents are found to destabilize the market. Furthermore, the observed stable sum of ARCH1 and GARCH1 around 1 indicates no change in the information flow, which might could have altered the volatility of spot market. A change in the volatility following a change in the information flow is not necessarily a negative finding, and relates the both Ross theorem 2 and the efficient market hypothesis. We thus accept out Hypothesis 2 (H_2) that some agents in the market affect the underlying spot volatility than other from their trading in derivatives. In addition, those companies with significant unexpected volume estimates have insignificant LM and LB-Q(6) tests, which indicate no further ARCH effects and that the model is well-specified those companies. From the GJR-GARCH model with expected and unexpected trading variables from test 8 we can therefore also accept Hypothesis 1; that the underlying spot volatility is affected by trading activities in derivatives.

4.2 Conclusion on the Results analysis

Test 1 and 2 was conducted to compare the goodness-of-fit and remaining ARCH effects with the results of the tests where we included trading activity variables. We also found evidence of the leverage effect and decided upon this finding to include this variable in the succeeding tests with trading variables. In general we found that the ARCH effects are appropriately captured by the GARCH and GJR-GARCH models and that both models has insignificant LB-Q test values, which indicate a satisfactory goodness-of-fit. However, the insignificance of both tests increases when trading variables are added, which suggest that the inclusion of these variables adds explanatory power to the model. The same results were found from Test 7 on asset level.

4.2.1 Index results

Hypothesis 1: From Test 3A and 3B we found evidence that trading activities in derivatives do affect the underlying spot volatility for the whole period when we both uses the GARCH and the GJR-GARCH model. The same results were found in Test 4, while our separation between types of types of derivatives in Test 5 decreased the explanatory power of the model substantially. Furthermore, the asymmetric effects of financial time series was documented and captured by the imposed leverage effect dummy variable, which indicates that the effect from trading activities was not confused by the leverage effect. ***Based on Test 3 and 4 we can therefore accept H_1 on index level.***

Hypothesis 2: The separation of derivatives trading variables into open interest and volume as approximations for hedgers and speculators trading activities respectively made it possible for us to test whether some agents in the market affected the underlying volatility more than others. From Test 3 we found a difference in the sign of the coefficients for open interest (+) and volume (-) for the whole period, which indicates that speculators trading activities tend to increase the underlying volatility. Also the net effect of the trading variables is found to be positive for the whole period for Test 3, while the net effect is found to be negative for Test 4. Unexpected shocks from speculators have the greatest positive effect on the underlying volatility, while unexpected open interests have the greatest negative effect on the underlying volatility. This supports the MDH and contradicts the dispersion of believes hypothesis. In sum, we find from Test 3 and 4 that speculators tend to destabilize the underlying volatility while hedgers tent to stabilize the underlying volatility (at least in the whole period). ***We therefore accept Hypothesis 2, that some agents affect the volatility more than others from their trading in derivatives.***

Hypothesis 3: In Test 5 we separated the trading activities into types of derivatives of different agents. Our results are found to be insignificant for all types of derivatives, which suggest that the overall derivatives trading, is the only proxy for explain the underlying volatility. ***We reject Hypothesis 3 on basis of the results from Test 5 and conclude that separation in types of derivatives decreases the explanatory power of the model.***

Hypothesis 4: From Test 3 and 4 we find evidence of changing sizes and signs of the coefficient estimates of the derivatives trading variables. Many of them are found insignificant for sub-periods, especially in Test 4, while we in Test 3 concluded that open interest tends to destabilize the market in bear market, but stabilize the markets in bull markets. In contrast, the volume variable is found to increase the underlying volatility in all market conditions. ***However, the insignificance of the estimates makes us reject hypothesis 4; that the effect from derivatives trading changes in accordance with the market conditions.***

4.2.2 Asset results

Hypothesis 1: The results for Test 7 were for the derivatives trading variables found insignificant, which suggested rejection of H_1 and H_2. However, in Test 8 we found strong evidence of a positive relation between unexpected volume and volatility for most of the analyzed stocks for the whole period. ***We therefore accept H_1 on asset level.***

Hypothesis 2: The unexpected volume, which is approximated to shocks from speculators trading activities, is found significant and positive for the whole period. This implies that speculators destabilize the underlying market, while the found insignificant trading estimates for the last three variables indicate no effect on the underlying spot volatility. At the same time we found the GARCH and the ARCH1 coefficients to be quite stable over time, which suggest that the information flow and its implication for the volatility has remained unchanged in the period. The increase in volatility can therefore only be advocated speculators trading activities in derivatives. Also the effect from noise trader's hypothesis supports this finding. ***We therefore accept Hypothesis 2; that some agents at the derivatives market affect the volatility more than others***

On asset level we did not tested for hypothesis 3 and 4. The last finding is of great interest in general and the results will be included in the following discussion and perspectives.

5 Discussion and perspectives

In the following we will shortly discuss our findings of the effect from trading activity in derivatives on the underlying spot volatility in a more general perspective, which will include the implication on welfare in an economy, efficient markets and information flow, and regulatory perspectives. We also discuss other factors that may affect and dominate the underlying volatility in spot markets and include subjects for future research.

Both in Test 4 and 8 we found evidence of a destabilising effect from unexpected trading shocks from speculators. The evidence is especially profound for Test 8 (asset level), where most of the companies exhibit highly significant and positive coefficient estimates for unexpected volume. In the same test we found insignificant hedgers activities, which were approximated to open interest, and could therefore conclude that speculators destabilise the underlying spot volatility. The discussion of the effect of derivatives trading activities on the underlying spot volatility can be seen from many perspectives. Opponents with a regulatory perspective argue that increased volatility from derivatives trading activities also alter and harms the real economy, and thus decrease the total welfare in the economy.[134] Also the lower transactions costs attract speculators, who reinforce the negative effect on the economy by their derivatives trading.

In contrast, proponents of derivatives markets argue that the social benefit from derivatives markets is substantial since it provides insurance for financial intermediates and market participants. Furthermore, they view financial markets as being efficient where all information should be reflected in the current prices. This eliminates any volatility increasing actions from speculators due to lack of encouragement of speculation since no private information would be left to create excess return.[135] The proponents also strongly advise regulated markets to be loosened.

For the Swedish market a relation between the excess stock market volatility caused by derivatives trading and its effect on the real economy need to be established to draw any conclusion upon regulatory initiatives. We therefore suggest this field of study for future research. However, the introduction of Security Transaction Taxes in Sweden in 1983 serves as

[134] Grossmann (1977); p. 447
[135] Grossmann (1977); p. 446

an example of possible consequences of imposing taxes or regulations on the Swedish market, where most of the trading activities mitigated to the London Stock Exchange.[136]

Another interesting field of study for future research could be how the quality and the dispersion of information arrival on the derivatives markets affected the underlying spot market. Also whether any optimal information amount exists or what kind of information market participants finds relevant.[137] This issue has become increasingly important following the arrival of information technologies that has increased the pace of information mitigation from one market to another.

In our thesis the main subject has been the effect from derivatives trading on the underlying volatility and we have therefore ignored any other external factors / variables that might affect and/or explain the volatility of the underlying market. Theoretical models and tests have especially been concentrated around joint effects of leverage and macroeconomic volatility, stock returns (momentum), long term - and short term interest rates, inflation rates, money supply and financial leverage.[138]These models have a longer horizon and tend to explain the overall long-term volatility and consist of lower frequency data sets. These models are thus ill-suited for higher frequency financial data.

Since our results are specific to the Swedish market we cannot draw any conclusion on whether derivates trading yields the same effect in similar markers (this is strongly supported by the ambiguity from our section about previous research of stochastic volatility). An interesting angle for future research could therefore be whether the size of the market has any effect on the relation between the underlying spot volatility and trading activities. However, such an investigation would be very extensive and probably not yield any clear answers due to the differences in the microstructure of financial markets.[139]

From our empirical testing we found that some of our test results depend on the econometric model used (all models applied have nevertheless been GARCH-type of models). The inclusion of derivatives trading variables was significant for some and not for others. The inclusion of other

[136] Harbermeier & Kirilenko (2003); pp. 87 – 91
[137] Dawson & Staikouras (2009); pp. 1.208.
[138] Schwert (1989); p 1.143 – 1.150.
[139] Kapoff (1987); 123

stochastic volatility models would require extensive computation, but would be interesting in future research. Comparison of different models would thus make it possible to evaluate which model that would yield the best results. Furthermore, this knowledge would be useful in option trading strategies as an alternative to the implied volatility often used, but again rather complicated and extensive.[140]

Finally, from our research of the Swedish market we found that the vast majority of derivatives trading are carried through by the NasdaqOMX, who acts as clearing for the Nordic OMX exchanges. An Overt-the-Counter (OtC) trading activity thus only stands for an insignificant trading. Also the liquidity in the OtC market for derivatives is substantial smaller compared to the OMX liquidity. For future research the effect from OtC derivatives markets on the underlying volatility in countries with a more developed and liquid OtC market could be an interesting angle of investigation. Also the effect from trading activities in black/gray pools should be investigated further to shed light on how destabilising these types of trading are for the market and for the real economy. Those kinds of researches would help regulators to make better future decisions about the microstructure of financial markets and regulation.

[140] Juttmann (2007)

6 Conclusion

In this thesis we have investigated how derivatives trading activity affects the underlying volatility and whether we could find any relation between derivatives trading activity on the Swedish major index, OMXS30, and on selected components stocks. To answer our main research question we build our investigation on three major pillars; a *Theoretical framework*, an *Empirical model specification* part and *Empirical test and result analysis.*

From our Theoretical framework we investigated how different agents in the derivatives market affect derivatives trading. We identified three types of traders; *Arbitrageurs, Speculators* and *Hedgers*. The effect from arbitrageurs are found small and insignificant do to the increasing efficiency of financial markets, while trading activities of speculators and hedgers are more effective on the derivatives market. Hedgers mainly use derivatives to manage risk from long positions in the market, which is the one of the fundamental purposes of derivatives markets. In contrast, speculators take positions in derivatives to earn a higher return on investment by not holding the underlying asset. Thus their investments are leveraged, which in theory has a destabilising effect on the underlying market.

To investigate the theoretical effect from different agents in the derivatives market and the role of information for the price formation, we investigated the relation between information, trading volume and volatility from various information hypotheses. We identified four important hypotheses; the Mixture of Distribution Hypothesis, the Sequential Arrival of Information Hypothesis, the Dispersion of Believes and the Effect from Noise Traders. All four hypotheses suggested a positive relation between the information flow and the trading volume, while the effect on volatility was found more ambiguous. Both the MDH and the SAIH do not distinct between hedgers and speculators, while both the Dispersion of Believes and the Effect of Noise Traders does. For the latter two a positive relation between volume, volatility and information flow was found. We used the acquired knowledge about the information flow to put our results in a broader perspective.

From research of modelling conditional volatility we found that two models are most dominant; the Stochastic Volatility Model (SVM) and the Generalised Autoregressive Conditional Heteroscedasticity model (GARCH). Both models were found appropriate in dealing with in-sample modelling of stochastic processes. We selected a GARCH-type of model due to its closed form solution and the popularity in other researches.

From investigating the stylized facts of the data we found evidence of volatility clustering, leptokurtosis and mean-reverting return series. These stylized facts of financial time series also support our choice of a GARCH-type model. An Autoregressive Moving Average (ARMA) element was added to remove the predictability associated with lagged returns, while a dummy to correct for the leverage effect was included. The ARMA process was investigated for each asset and the index to take into account individual statistical properties of each asset. Thus the GARCH-type model that best captures the characteristics of the data and employed in the rest of the thesis was an ARMA(p,q)-GJR-GARCH(1,1) model.

From the model we conducted several tests to answer our stated hypotheses. We separated the results into index results and asset results.

On index level we found that derivatives trading do affect the underlying volatility of the OMXS30. This was documented both for the whole period and for the subperiods. Also the leverage effect was found significant, which corresponds to the results in other researches. We also found that speculators' trading activities tend to increase the volatility, while hedgers were found to stabilise the market. Especially shocks from speculators were found large and positive, while the overall effect from trading is negative due to a stabilising effect from hedgers. Our findings support the MDH and contradict the dispersion of believes, and we can thus conclude that some agents affect the underlying volatility more than others. In contrast, we do not find any evidence that some types of derivatives affect the volatility more than others. Finally, we also reject the hypothesis that derivatives trading activities changes in accordance with the market conditions and that the econometric model employed fits the entire period the best.

On asset level we only tested for the effect from trading activities in derivatives and whether some agents affect the spot volatility more than others. We found a large and positive relation between unexpected shocks from speculators and the underlying volatility for the whole period. We therefore concluded that derivatives trading do affect the underlying volatility and speculators are the agents in the market that affect the volatility the most.

In sum, derivatives trading do affect the underlying volatility in the case of the Swedish market.

Whether the destabilising effect on volatility from derivatives trading has an effect on the Swedish economy depends on the effect of the increased volatility on the real economy. Further research in this relation is needed to be done and should serve as basis for future regulatory decisions.

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7.3 Web

Harvard University; Statistics Jargon for Astronomers; http://hea-www.harvard.edu/AstroStat/statjargon.html

The Board of Governors of the Federal Reserve; http://www.federalreserve.gov/

SPSS Support; http://support.spss.com/ProductsExt/SPSS/Documentation/Statistics/algorithms/14.0/acf_pacf.pdf

8 Appendices

8.1 Appendix 1 – Ross' theorem 2, a formal proof

Proof of the no-arbitrage martingale where the variance in information flow equals the variance in asset prices, $\sigma_I^2 = \sigma_P^2$ (Ross 1989).

Asset prices are by Ross (1989) assumed to be a martingale and represented by the following differential equation:

$$\frac{\partial p}{p} = \mu_p \partial t + \sigma_p dz_p \tag{1}$$

Where P is the asset price, μ_P is the mean, σ_p the standard deviation and

z ~$N(0,1)$.

Furthermore, from Ross' Theorem 1 we have that: *"Expected return satisfy the following generalized security market line equation:"* [141]

$$\mu_p - r = -\text{cov}(p,q) \tag{2}$$

As with asset prices, information flow follows a martingale and can be represented by:

$$\frac{\partial I}{I} = \mu_I \partial t + \sigma_I dz_I \tag{3}$$

Ross also considers the terminal condition that the value of an asset at time T is given by the information at time T ($P(T) = I(T)$), for which the following pricing relationship must hold:

$$P(t) = ie^{(\mu_i - r + \text{cov}(q,i)(T-t))} \tag{4}$$

From (4) Ross obtain the following differential equation:

$$\frac{\partial p}{p} = \frac{\partial I}{I} - (\mu_I - r + \text{cov}(q,I)\partial t \tag{5}$$

And by substituting (1) and (3) into (5) we get the following:

$$\mu_p \partial t + \sigma_p dz_p = (r + \text{cov}(q,I)\partial t + \sigma_I dz_I \tag{6}$$

---

[141] Ross (1989) pp. 5

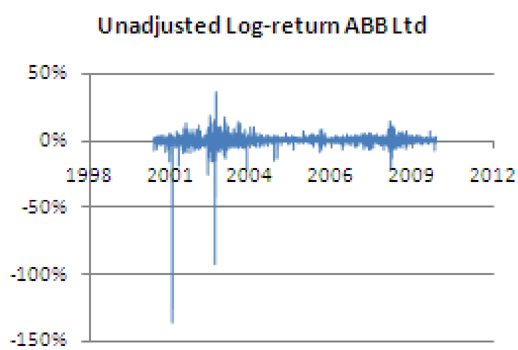
Finally, by substituting (2) into (6) we get:

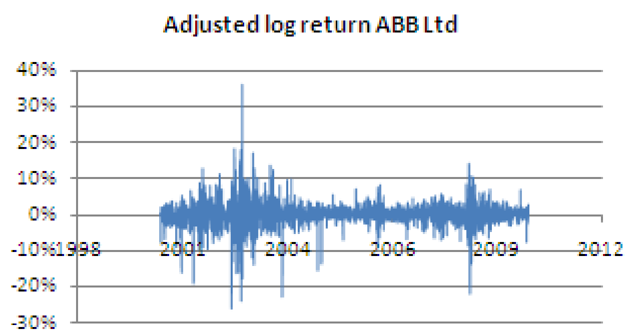
$\sigma_p dz_p = \sigma_I dz_I$, Which is the same as:

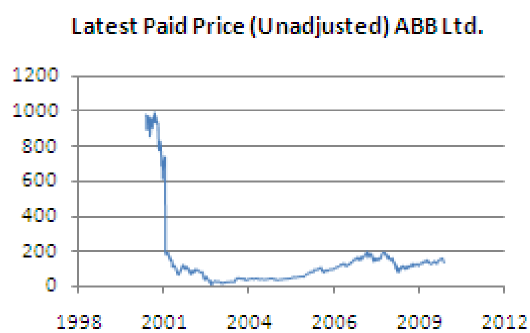
$$\sigma_p dz_p = \sigma_I dz_I$$

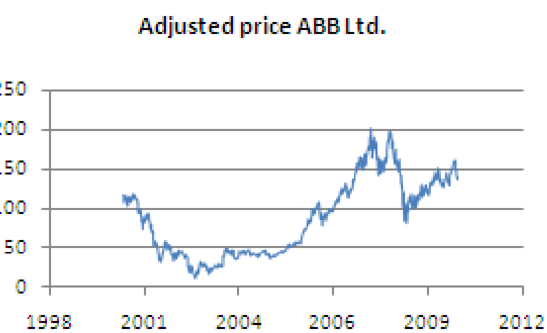
8.2 Appendix 2 – Return plots for analysed companies

ABB: Changed their outstanding numbers of shares twice in the analysed period. In late 2002 (official 2003) they issued new capital which resulted in 7:10 adjustment factor. In 2002 the company carried through a 4:1 split.

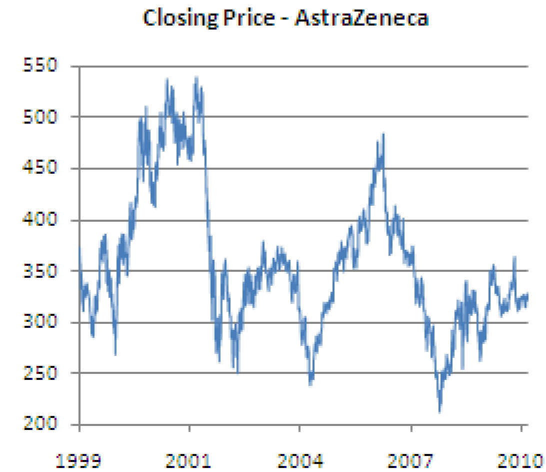


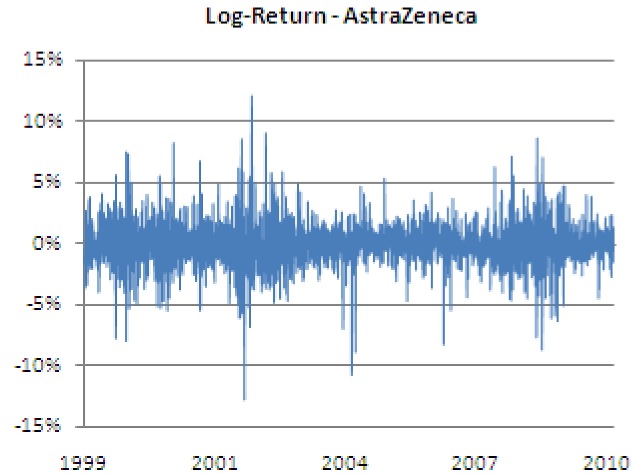


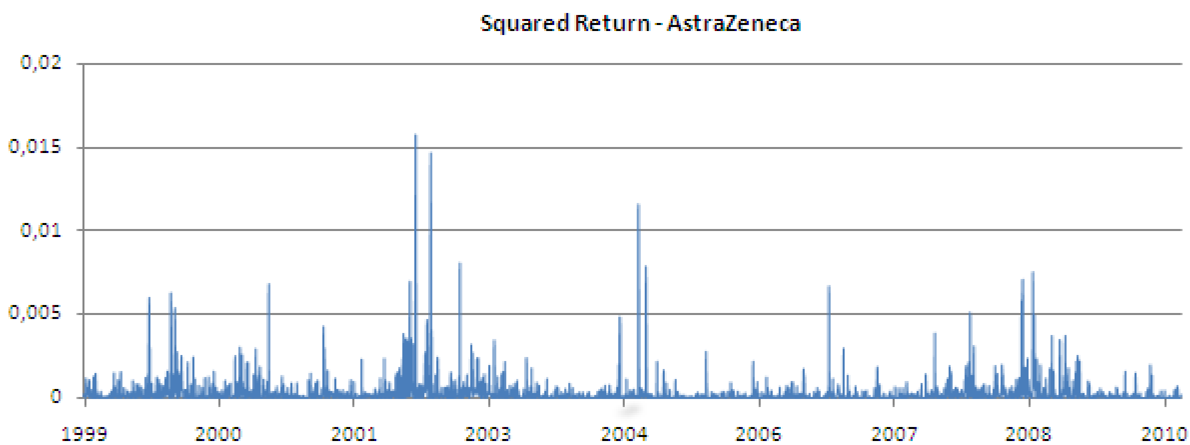




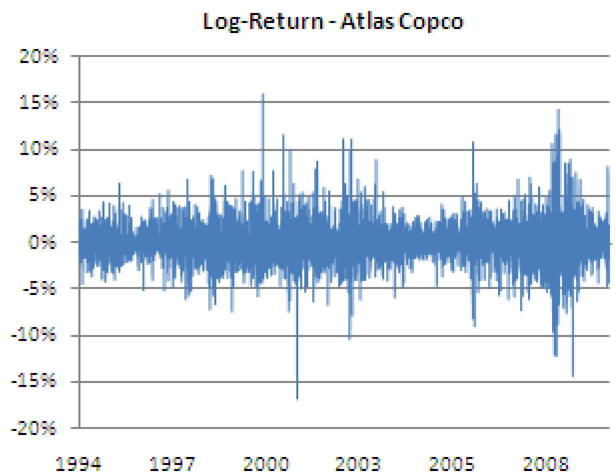
AstraZeneca: Observation period: From the 7th of April 1999 to the 24th of May 2010

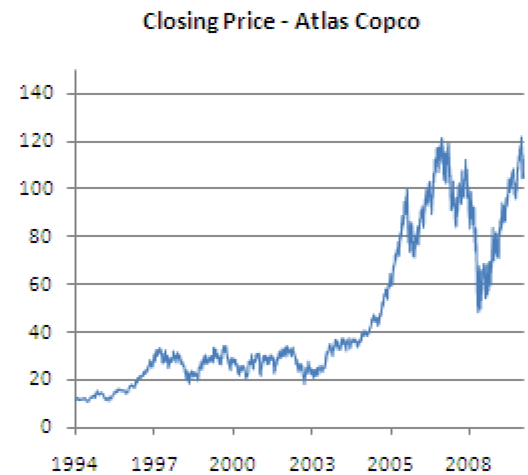


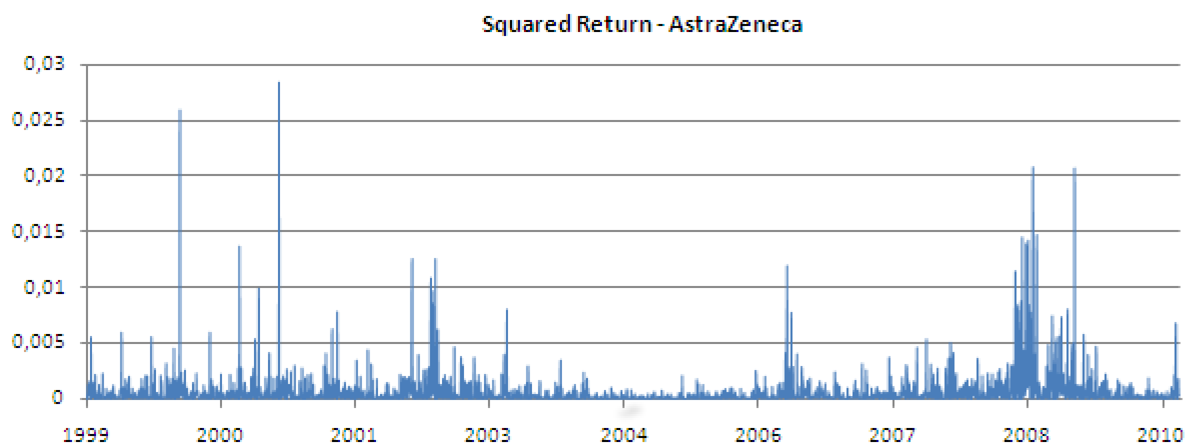




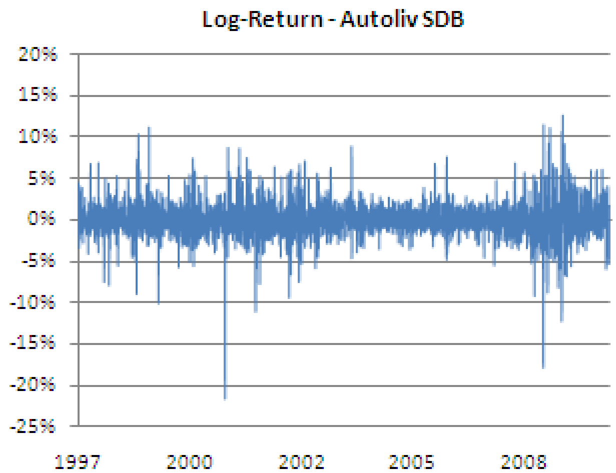
Atlas Copco AB: Analyzed period: From the 24th of October 1994 to the 24th of May 2010

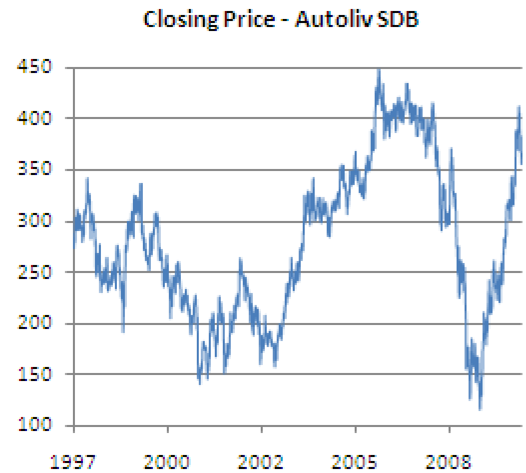


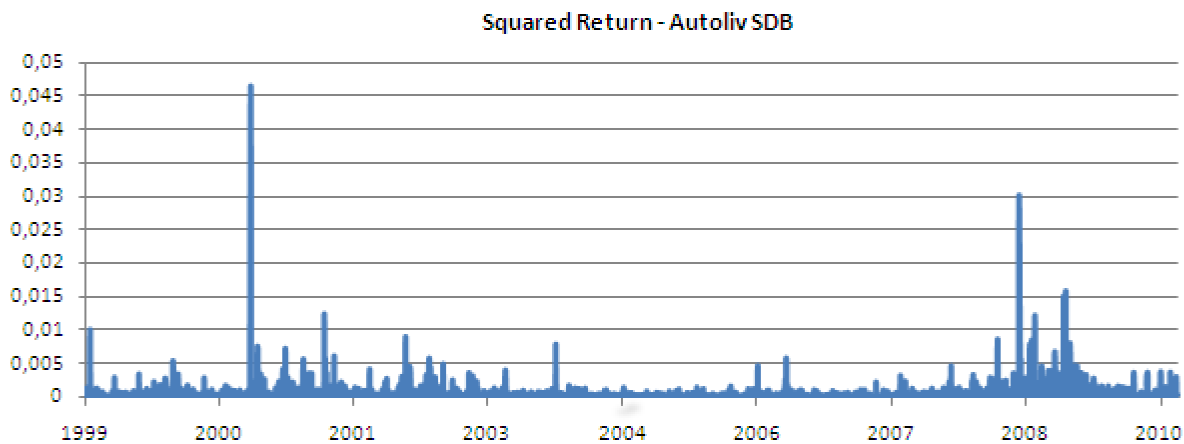




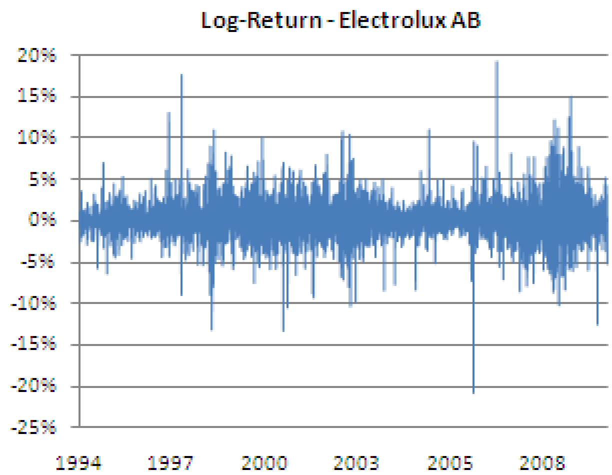
Autoliv SDB: Analysed period: From the 5th of May 1997 to the 24th of May 2010

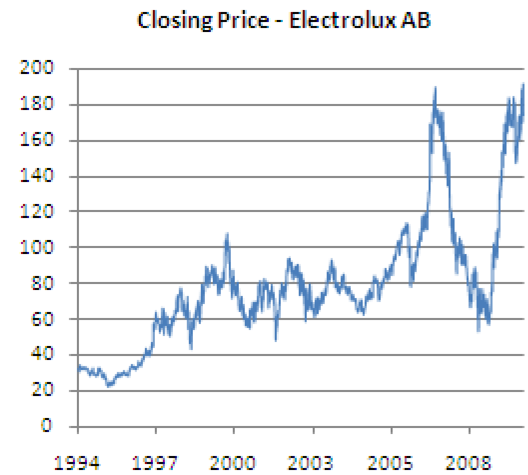


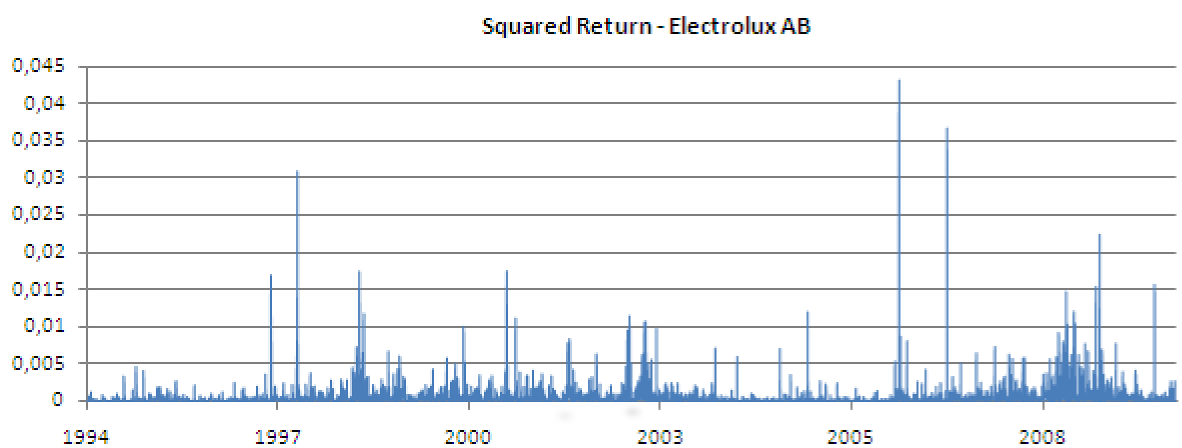




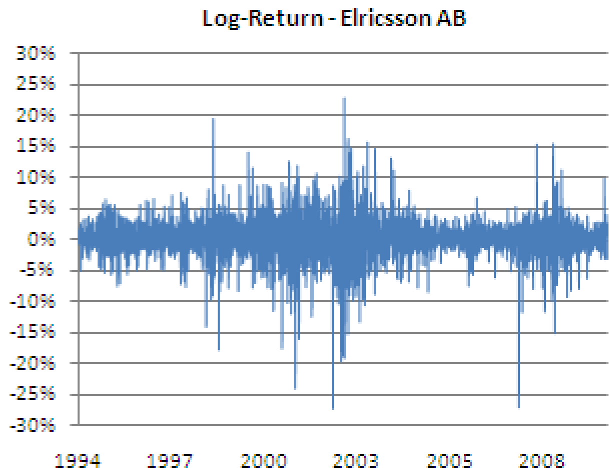
Electrolux AB: Analysed period: From the 25th of October 1994 to the 24th of May 2010

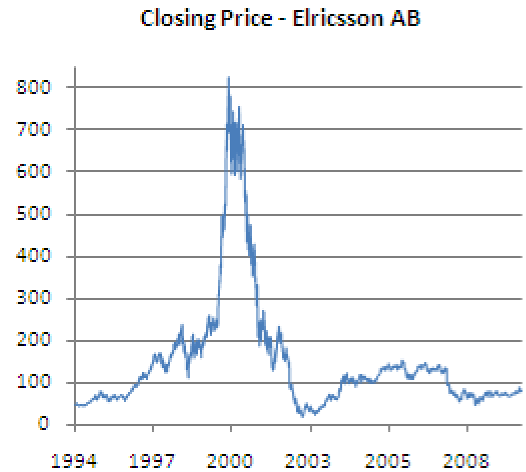


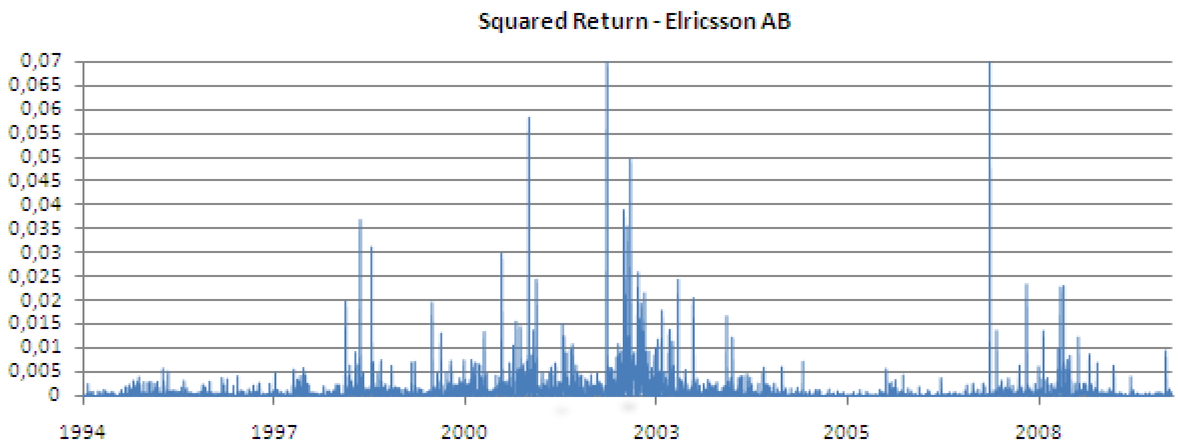




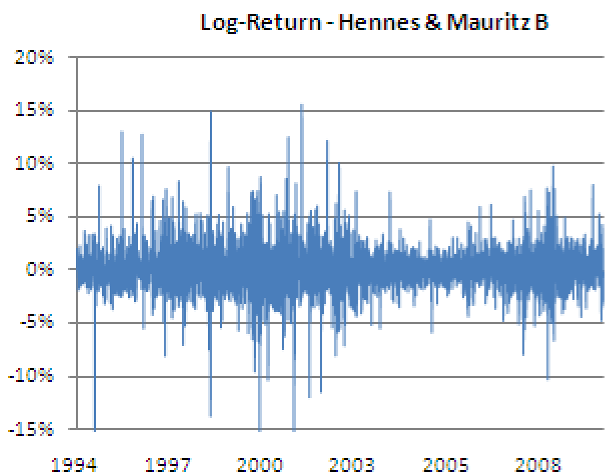
Ericsson AB: Analysed period: From the 25th of October 1994 to the 24th of May 2010

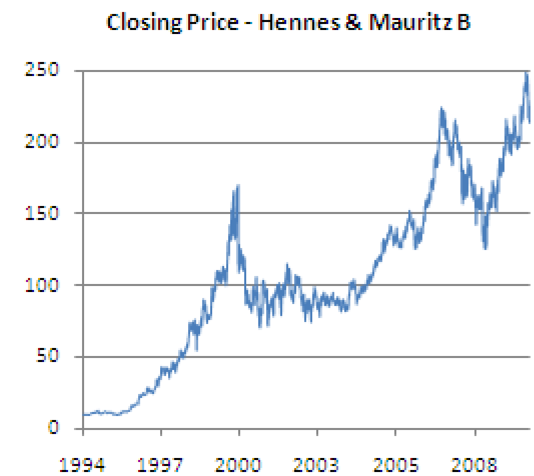


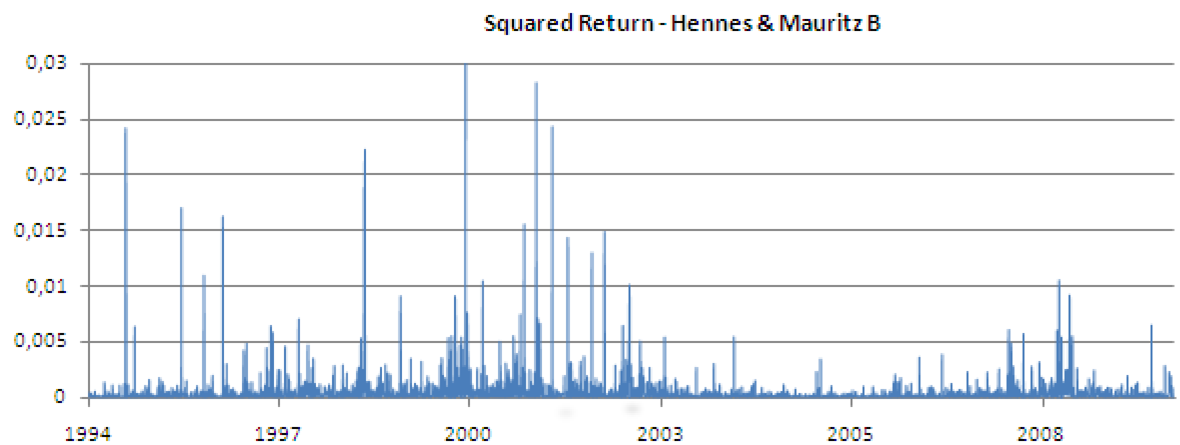




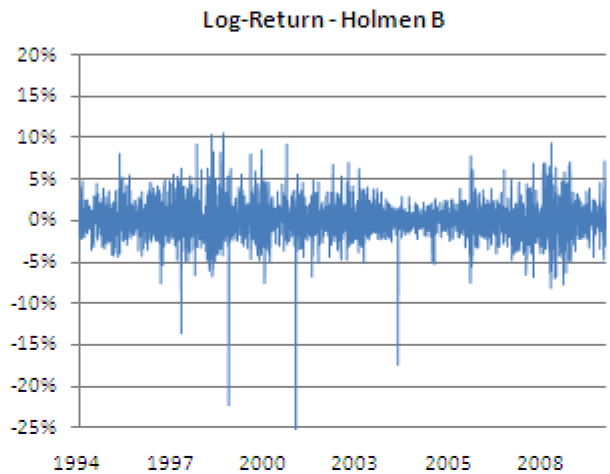
Hennes & Mauritz B: Analysed period: From the 24th of October 1994 to the 24th of May 2010

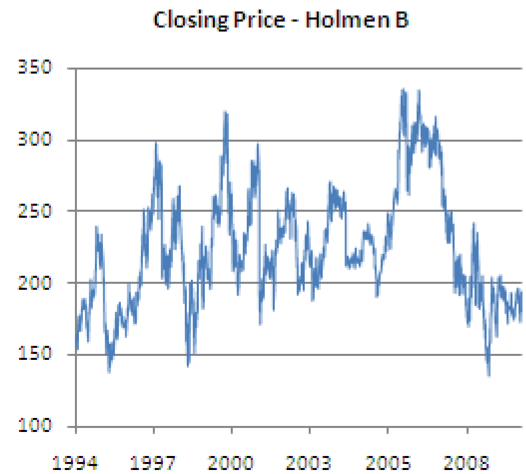


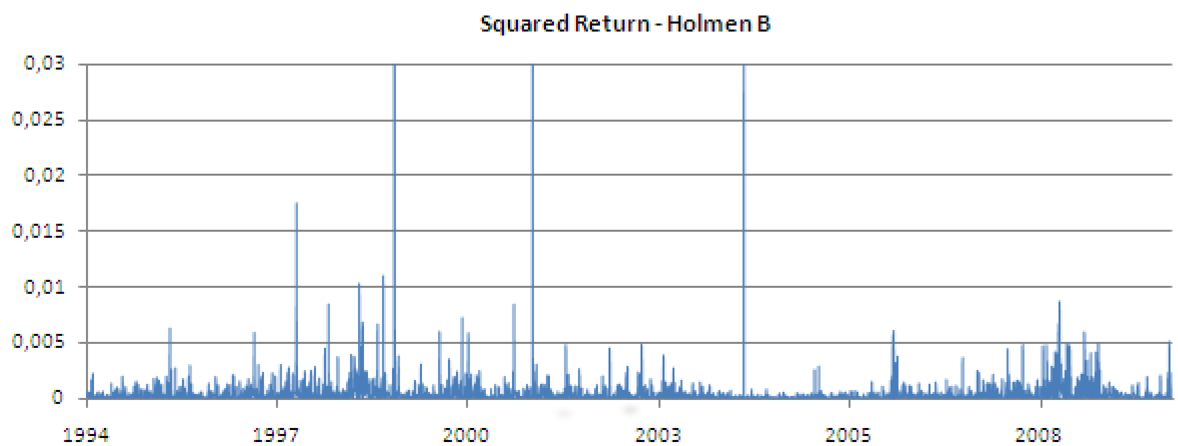




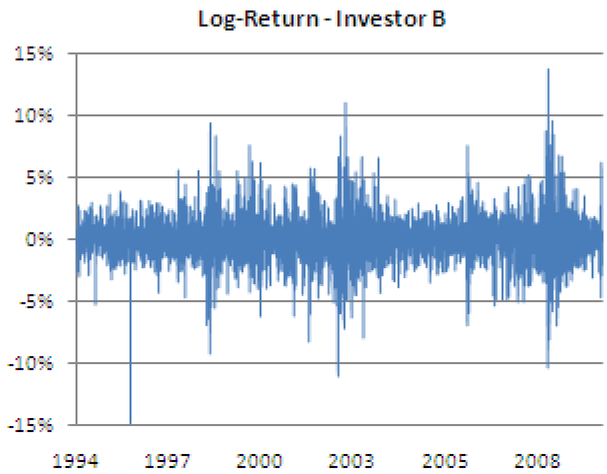
Holmen AB: Analysed period: From the 24th of October 1994 to the 24th of May 2010

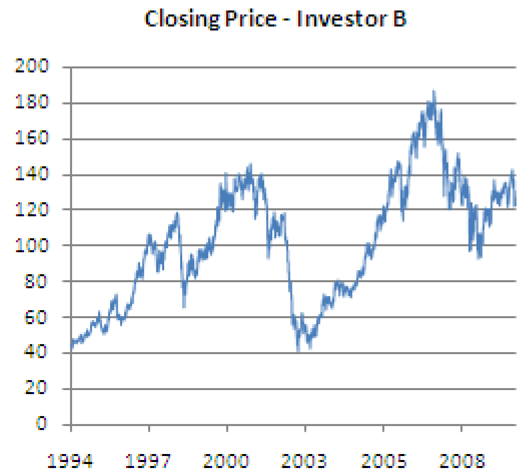


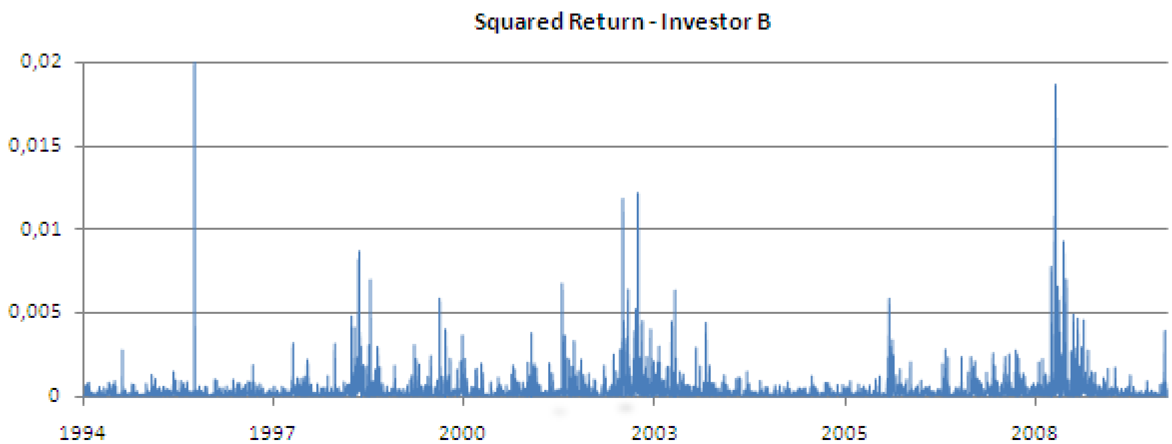




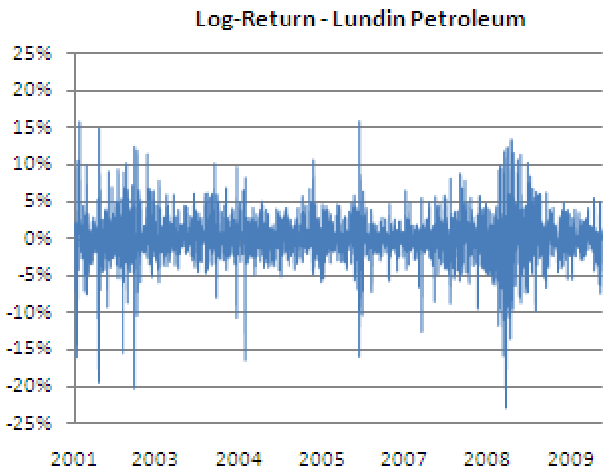
Investor B: Analysed period: From the 24th of October 1994 to the 24th of May 2010

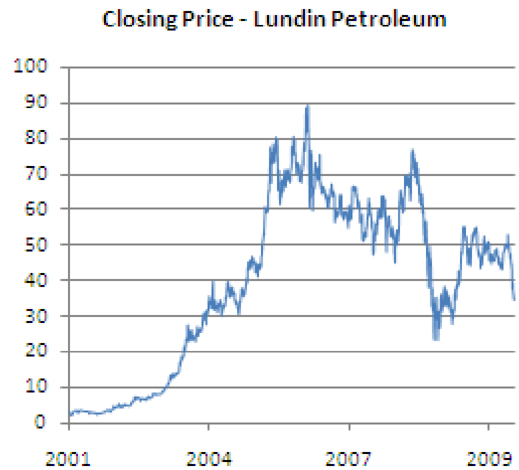


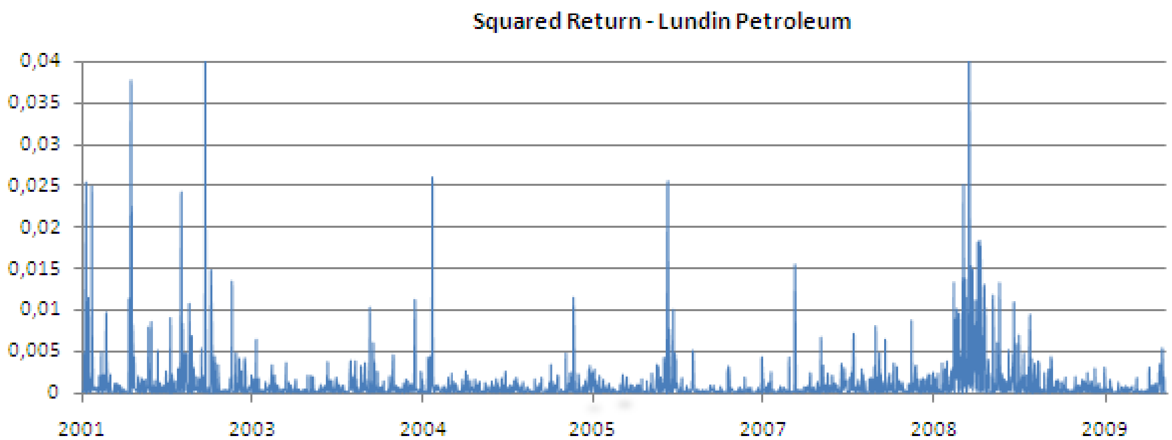




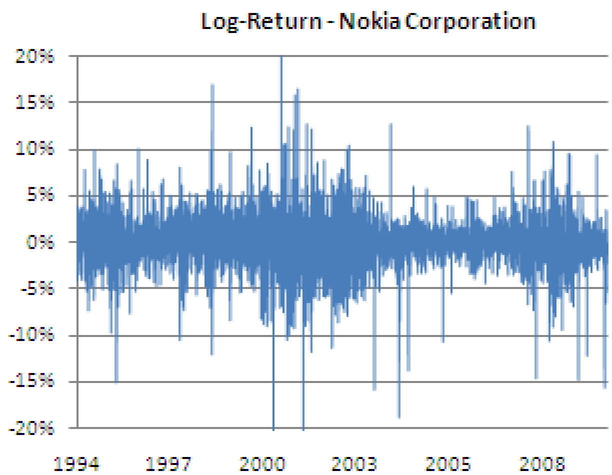
Lundin Petroleum: Analysed period: From the 6th of September 2001 to the 24th of May 2010

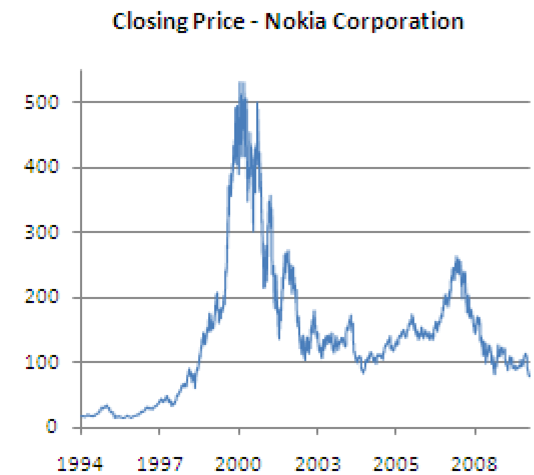


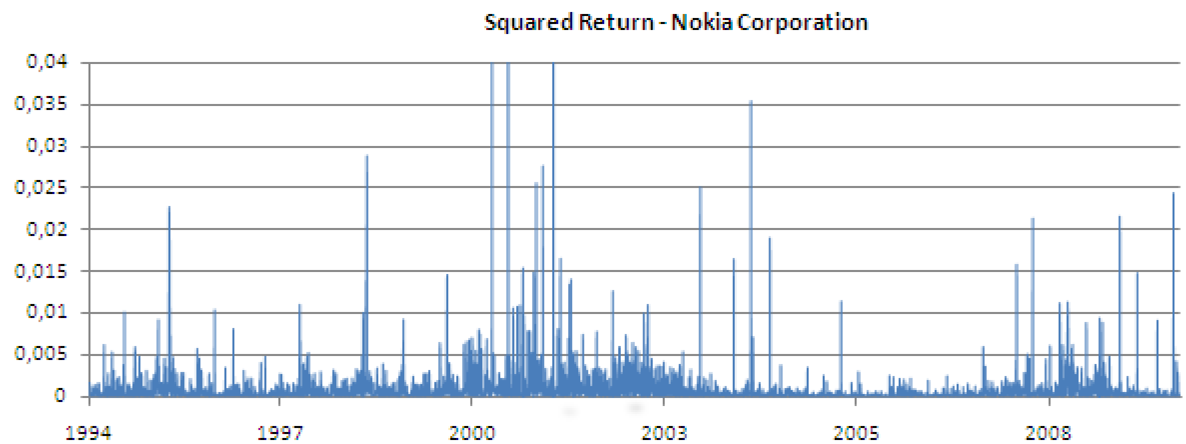




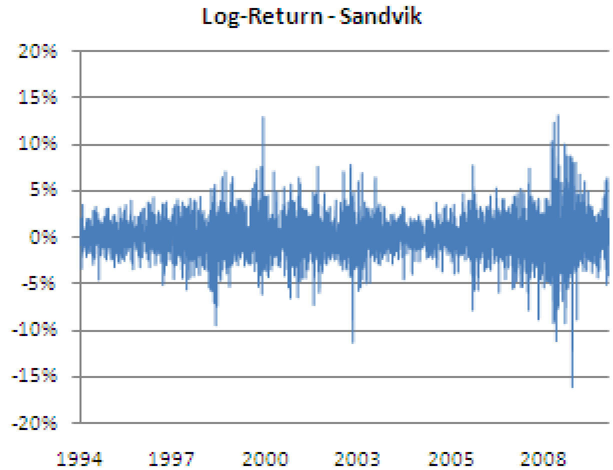
Nokia Corporation: Analysed period: From the 24th of October 1994 to the 24th of May 2010

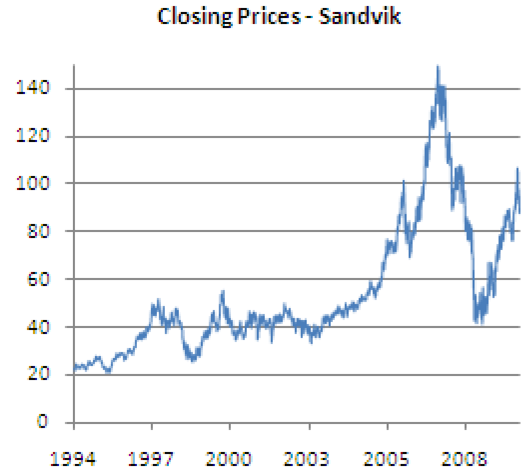


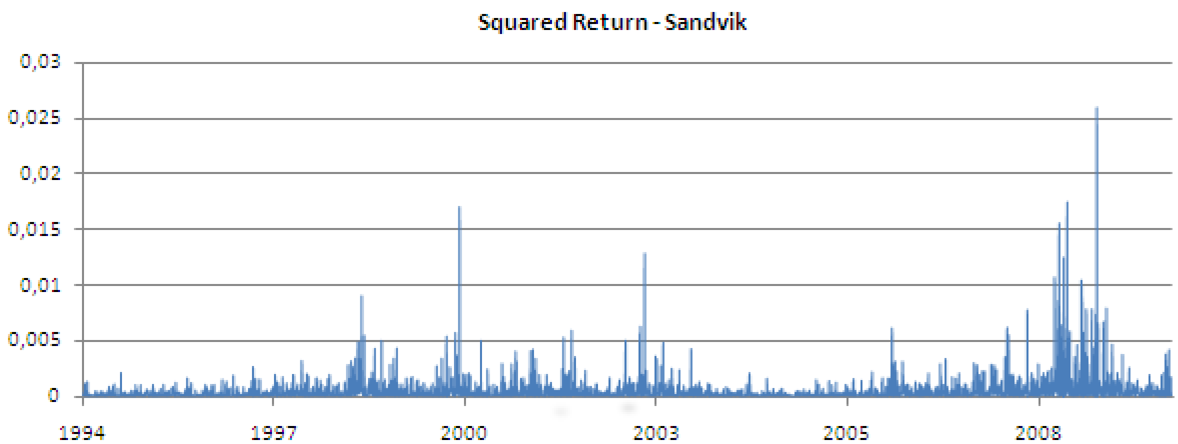




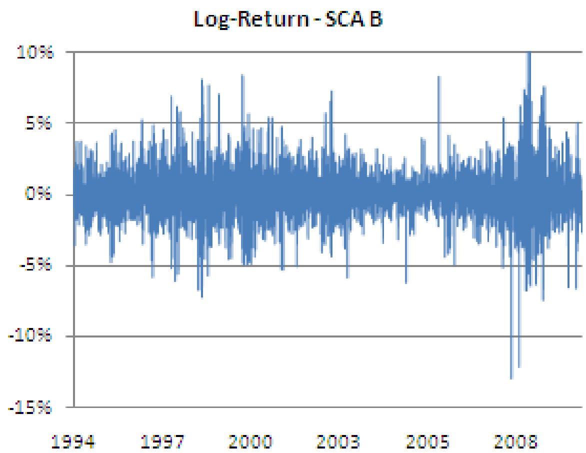
Sandvik: Analysed period: From the 24th of October 1994 to the 24th of May 2010

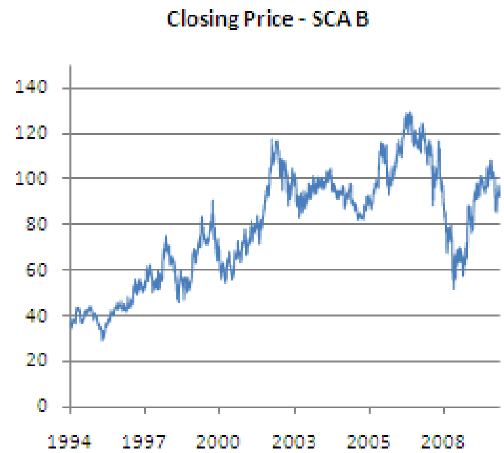


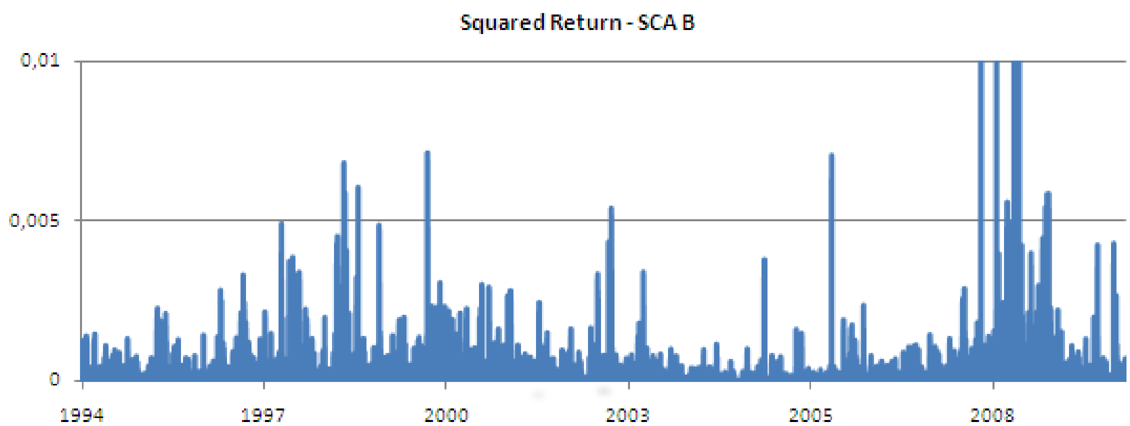




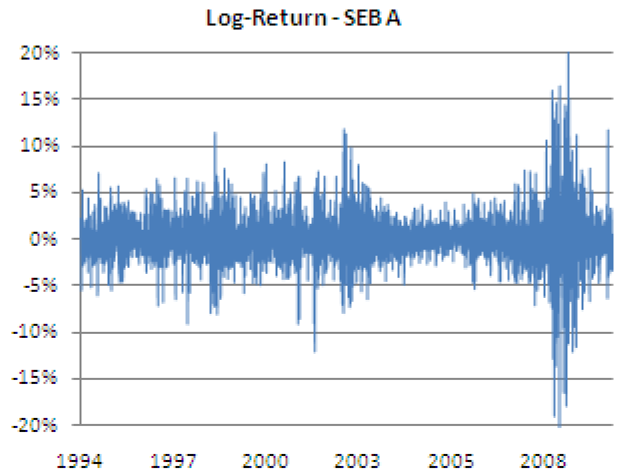
SCA B: Analysed period: From the 24th of October 1994 to the 24th of May 2010

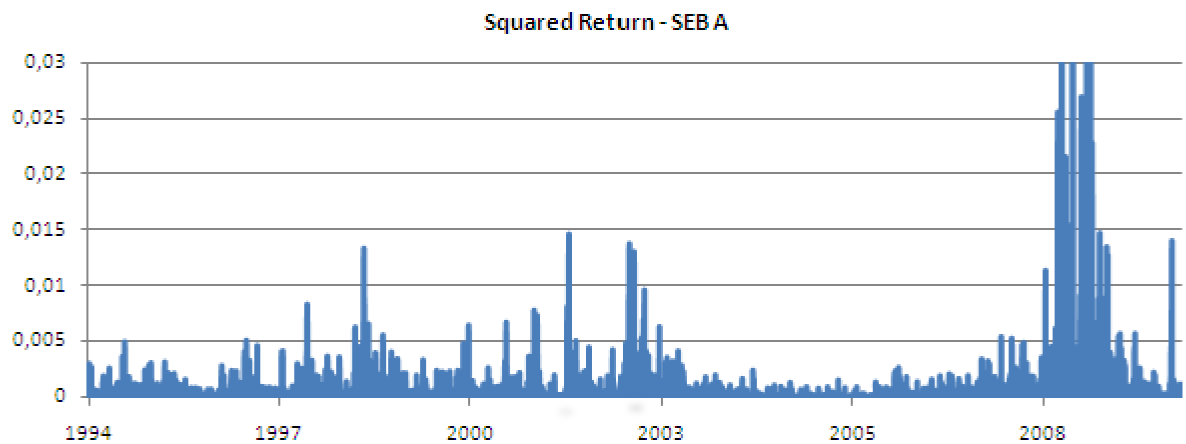




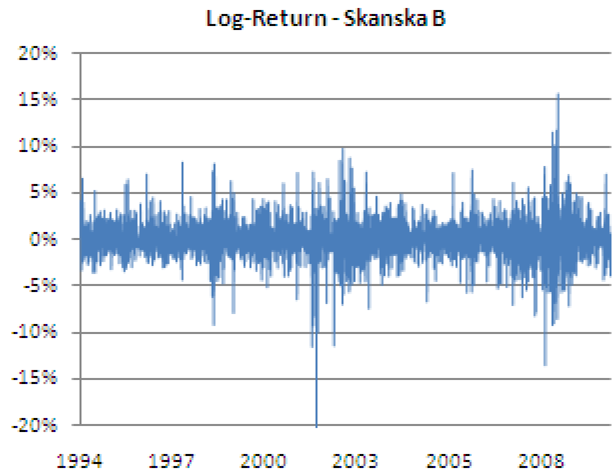


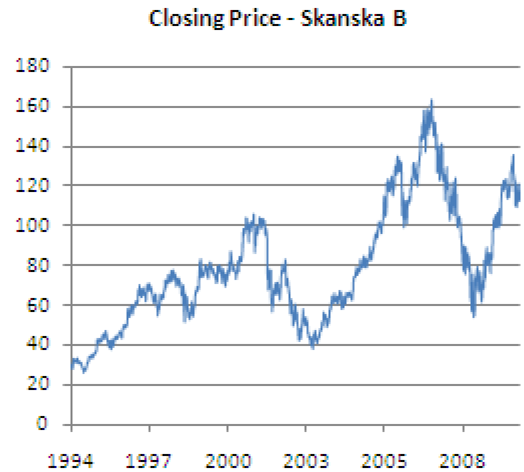
SEB A: Analysed period: From the 24th of October 1994 to the 24th of May 2010

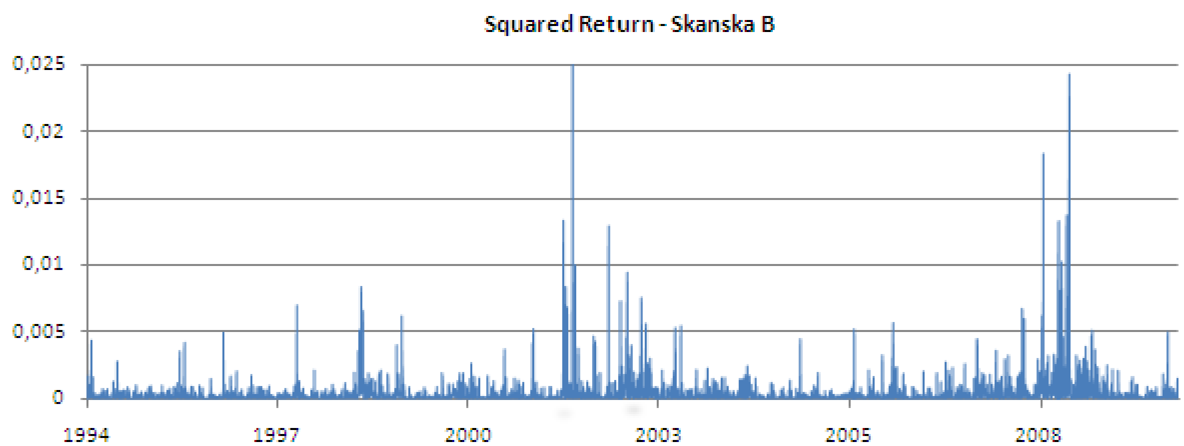




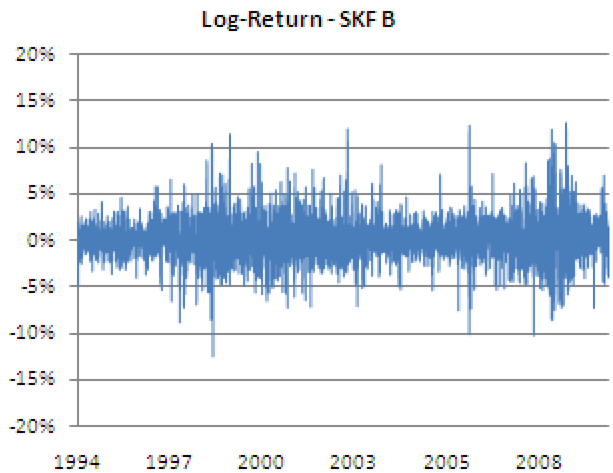
Skanska B: Analysed period: From the 24th of October 1994 to the 24th of May 2010

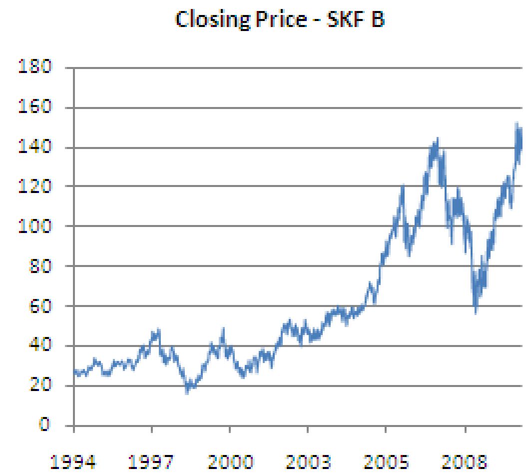


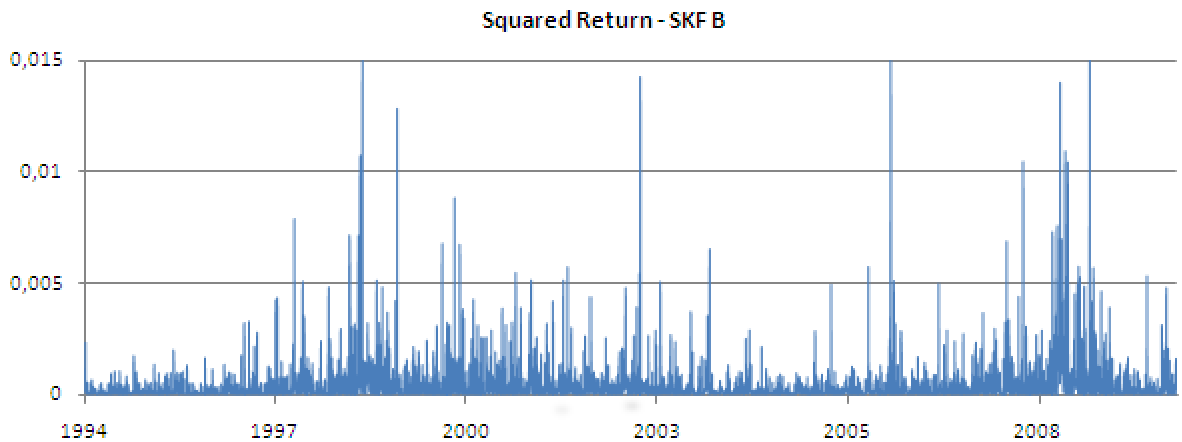




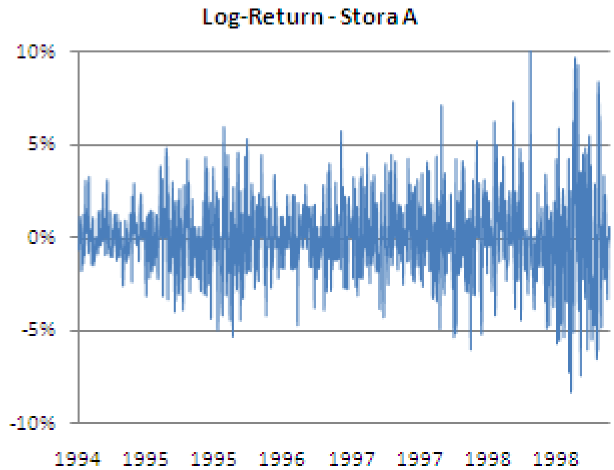
SKF B: Analysed period: From the 24th of October 1994 to the 24th of May 2010

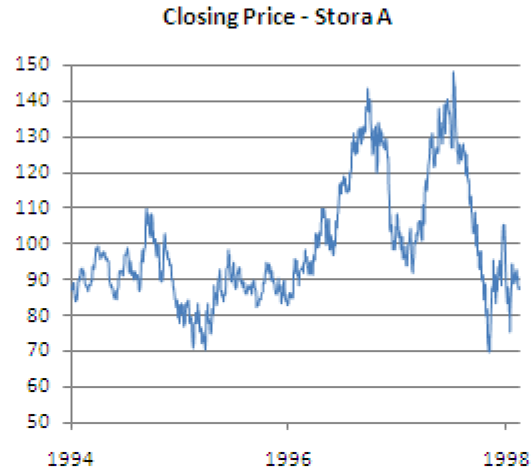


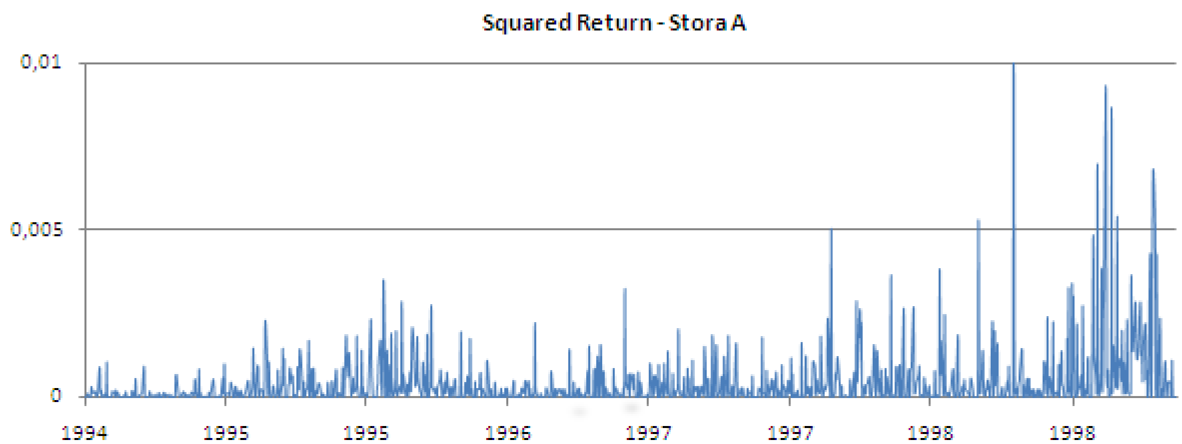




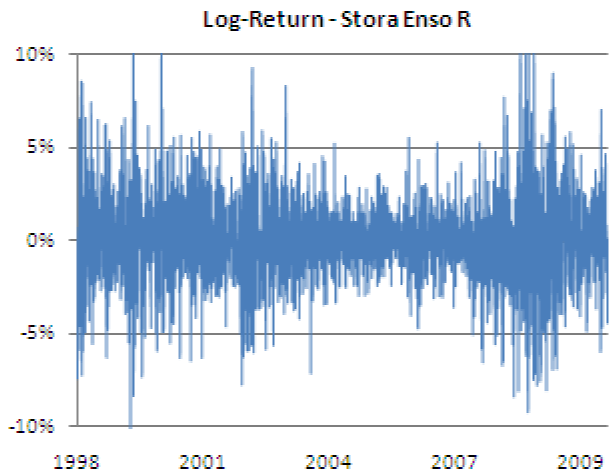
Stora A: Analysed period: From the 24th of October 1994 to the 19th of January 1999

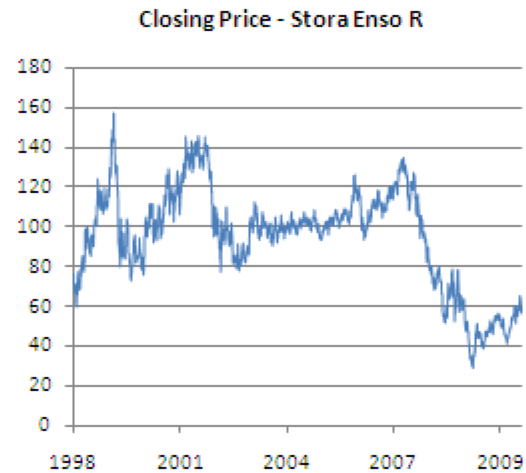


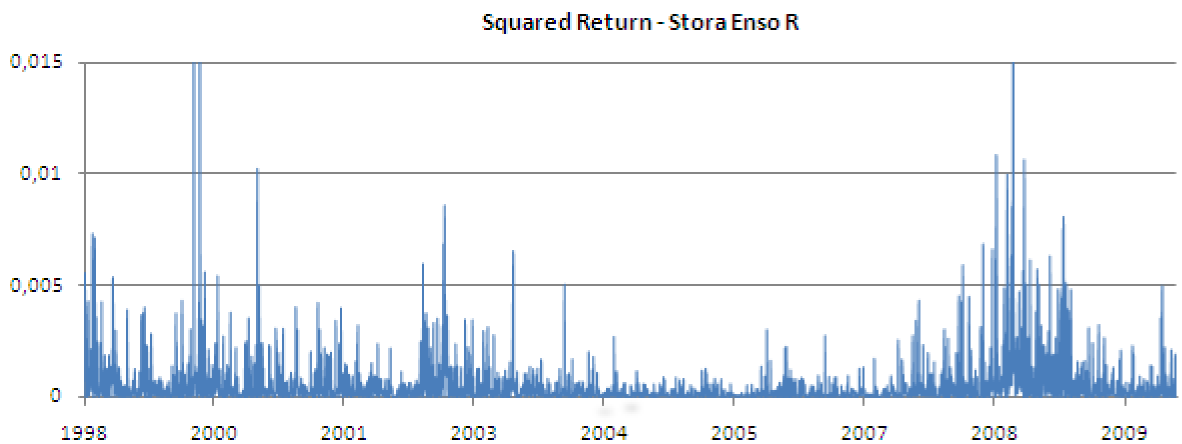




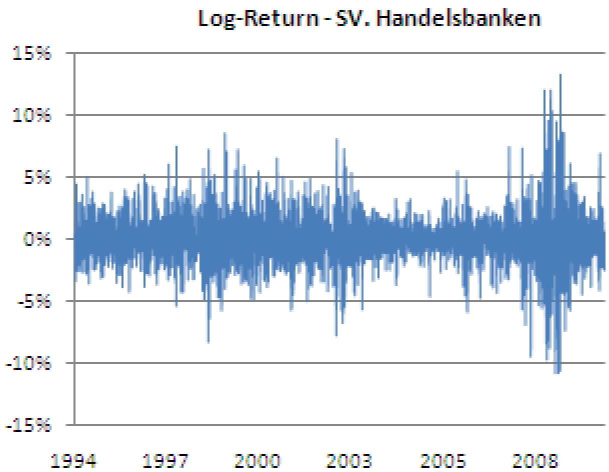
Stora Enso R: Analysed period: From the 28th of December 1998 to the 30th of June 2010

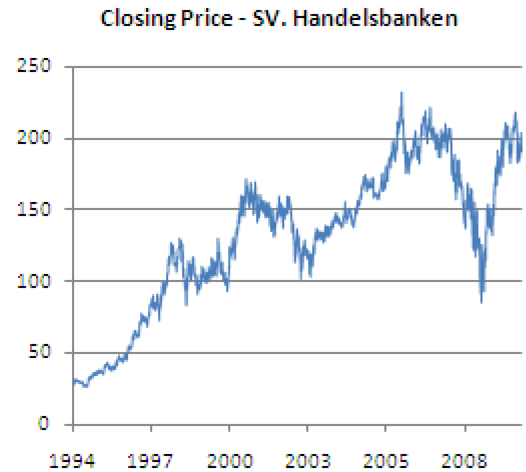


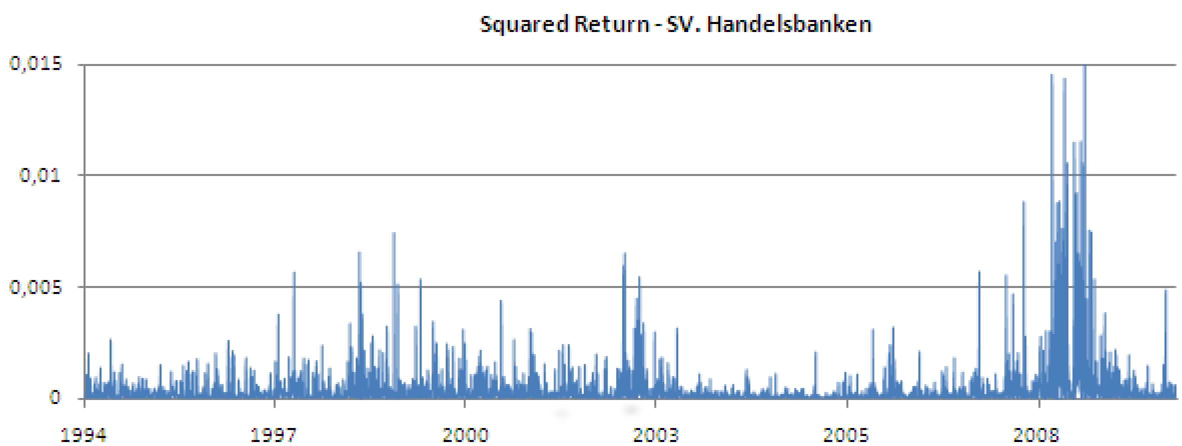




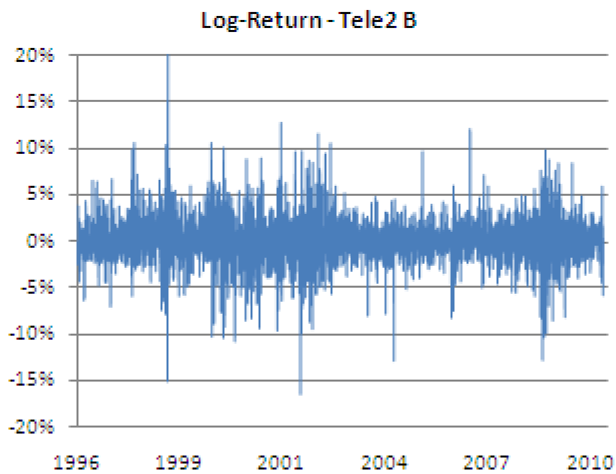
SV. Handelsbanken: Analysed period: From the 24th of October 1994 to the 30th of June 2010.

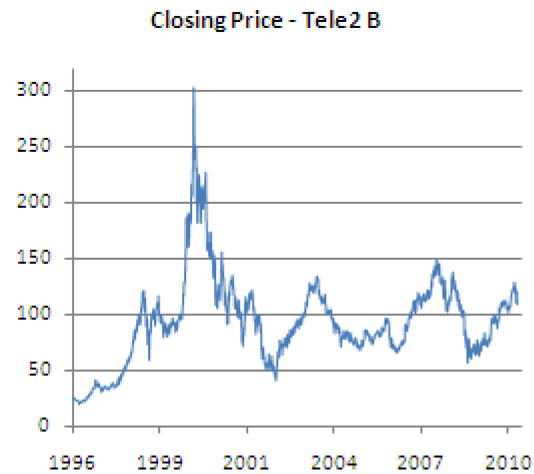


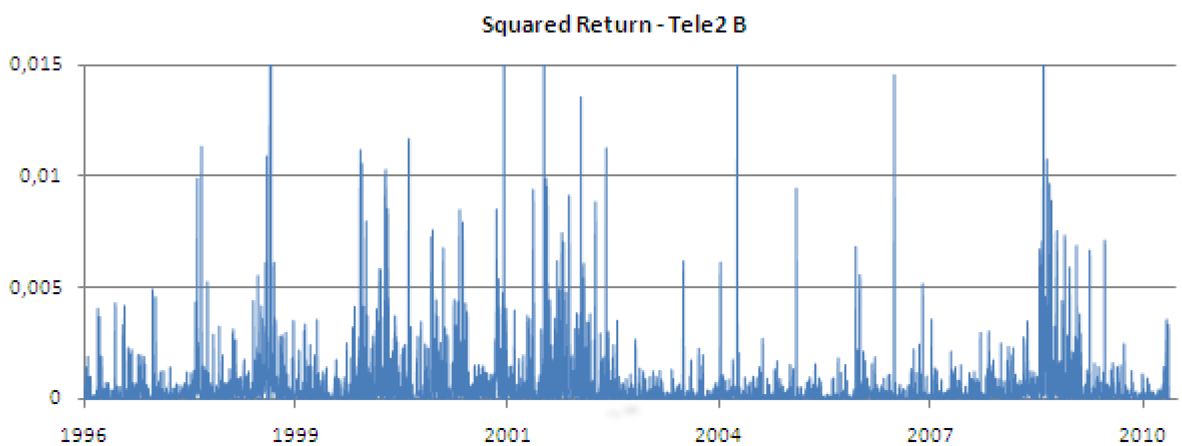




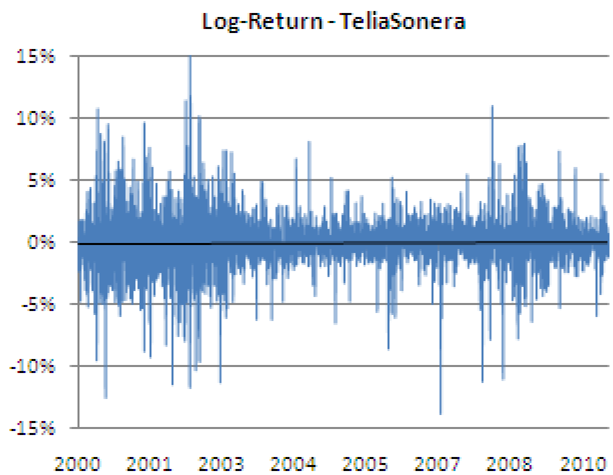
Tele2 B: Analysed period: From the 14th of May 1996 to the 24th of May 2010.

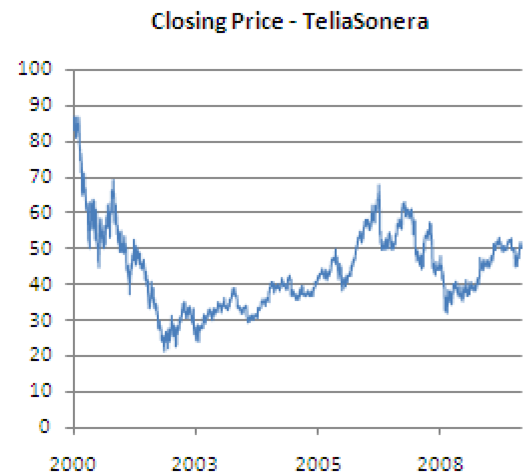


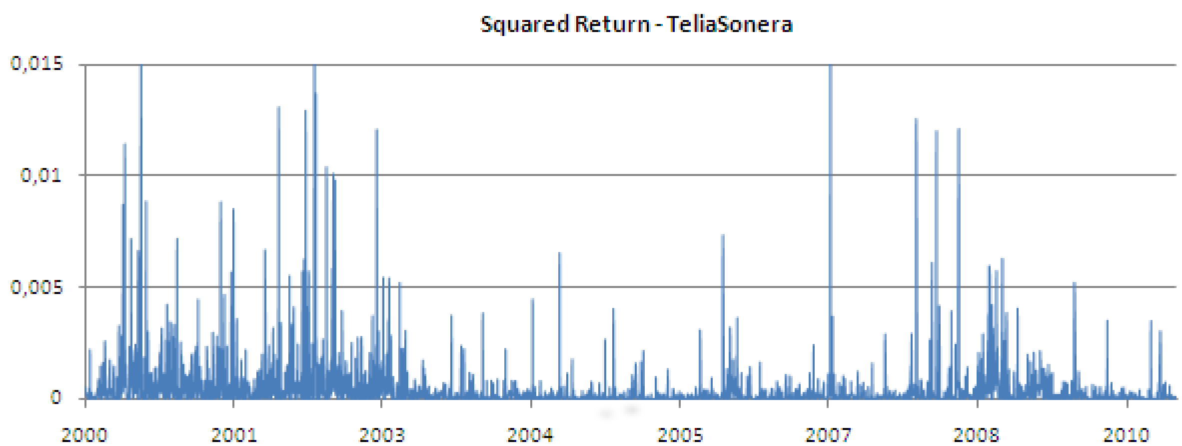




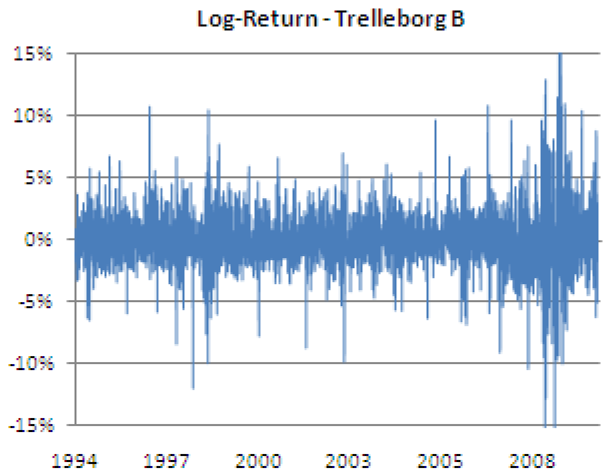
TeliaSonera: Analysed period: From the 13th of June 2000 to the 30th of June 2010

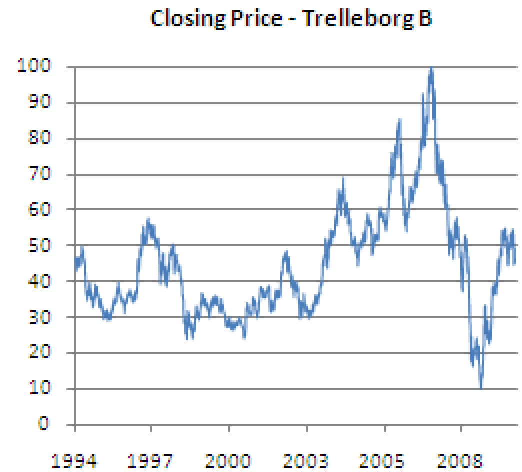


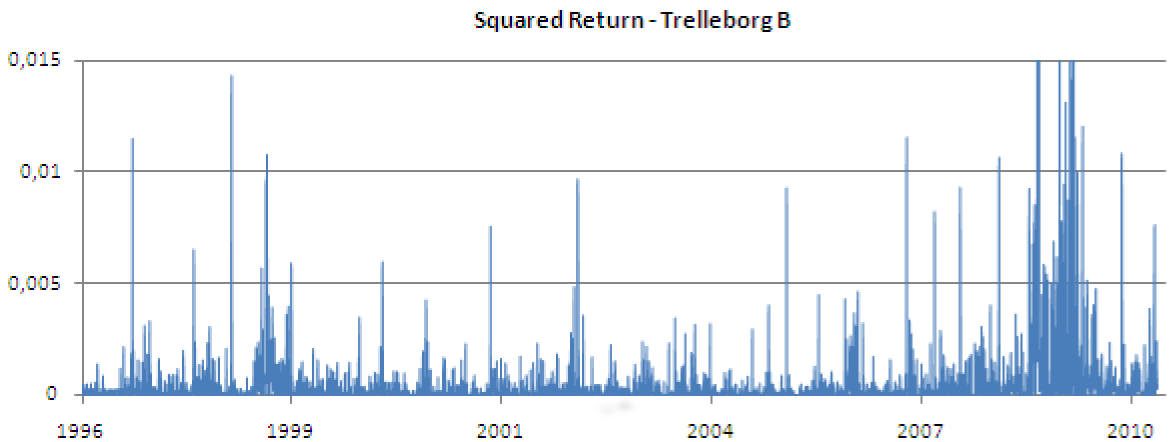




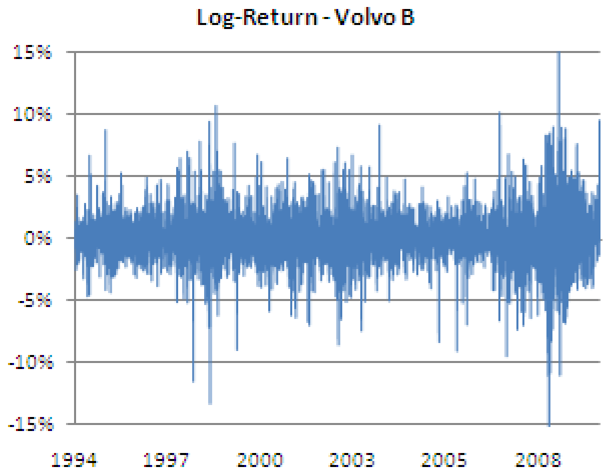
Trelleborg B: Analysed period: From the 24th of October 1994 to the 24th of May 2010

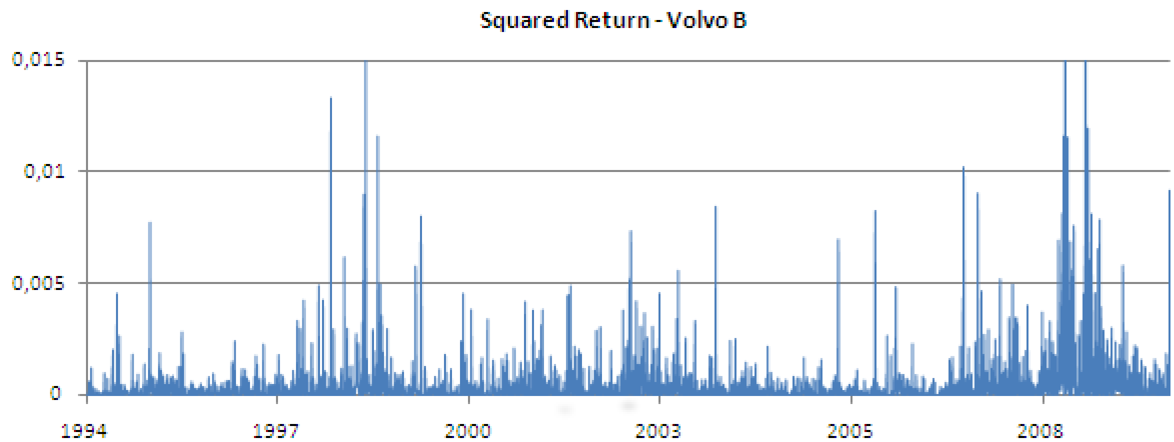






Volvo: Analysed period: From the 24th of October 1994 to the 23th of April 2010





8.3 Appendix 3 – Dickey-Fuller and Stationarity tests

Results for Augmentet Dickey-Fuller unit root test on OMX S30 and Electrolux daily returns. The p-value clearly rejects the hypothesis of non-stationarity.

Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	0	-4560.15	0.0001	-67.17	<.0001		
	1	-4916.29	0.0001	-49.57	<.0001		
	2	-5576.97	0.0001	-41.66	<.0001		
Single Mean	0	-4562.97	0.0001	-67.21	<.0001	2258.42	0.0010
	1	-4925.59	0.0001	-49.61	<.0001	1230.43	0.0010
	2	-5600.26	0.0001	-41.71	<.0001	869.88	0.0010
Trend	0	-4564.54	0.0001	-67.22	<.0001	2259.45	0.0010
	1	-4930.60	0.0001	-49.63	<.0001	1231.41	0.0010
	2	-5612.94	0.0001	-41.74	<.0001	870.92	0.0010

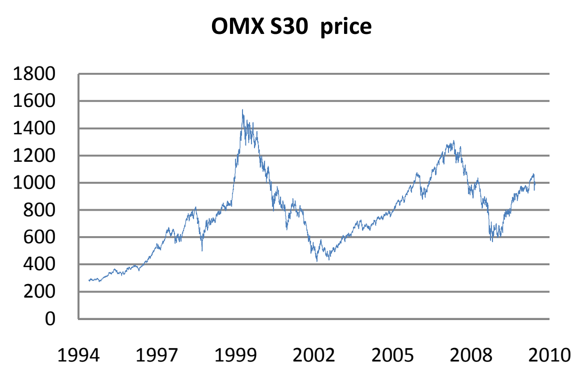
Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	0	-3948.93	0.0001	-61.96	<.0001		
	1	-4341.19	0.0001	-46.58	<.0001		
	2	-5016.81	0.0001	-39.36	<.0001		
Single Mean	0	-3950.11	0.0001	-61.97	<.0001	1920.32	0.0010
	1	-4345.02	0.0001	-46.59	<.0001	1085.48	0.0010
	2	-5026.94	0.0001	-39.38	<.0001	775.33	0.0010
Trend	0	-3950.12	0.0001	-61.97	<.0001	1919.86	0.0010
	1	-4345.07	0.0001	-46.59	<.0001	1085.22	0.0010
	2	-5027.09	0.0001	-39.37	<.0001	775.15	0.0010

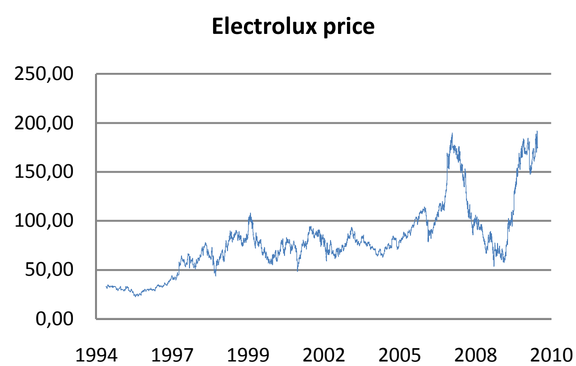
Results for Augmentet Dickey-Fuller unit root test on OMX S30 and Electrolux index prices/prices

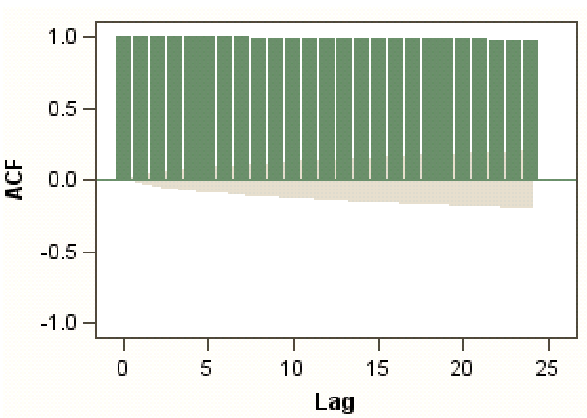
Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	0	0.2400	0.7408	0.22	0.7507		
	1	0.2790	0.7507	0.27	0.7634		
	2	0.3082	0.7582	0.30	0.7732		
Single Mean	0	-4.0988	0.5289	-1.61	0.4794	1.79	0.6118
	1	-3.8804	0.5532	-1.57	0.4963	1.77	0.6162
	2	-3.7244	0.5710	-1.55	0.5084	1.77	0.6180
Trend	0	-6.7637	0.6837	-1.85	0.6833	1.80	0.8164
	1	-6.3164	0.7197	-1.78	0.7141	1.70	0.8380
	2	-5.9977	0.7451	-1.74	0.7355	1.62	0.8532

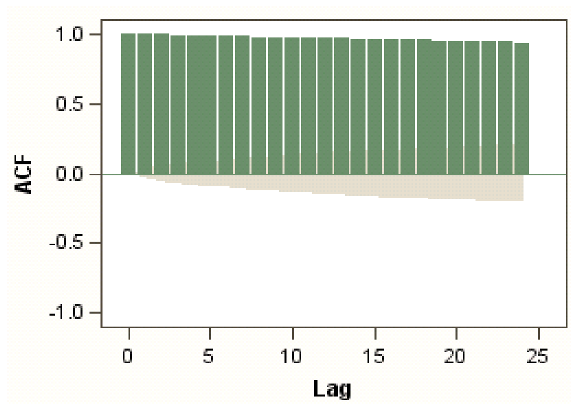
Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	0	0.7737	0.8714	0.50	0.8245		
	1	0.7742	0.8715	0.51	0.8246		
	2	0.8771	0.8919	0.60	0.8456		
Single Mean	0	-4.2600	0.5113	-1.14	0.7026	1.22	0.7593
	1	-4.2459	0.5128	-1.13	0.7045	1.21	0.7612
	2	-3.6586	0.5786	-1.02	0.7467	1.14	0.7780
Trend	0	-15.2643	0.1766	-2.58	0.2886	3.53	0.4656
	1	-15.2981	0.1755	-2.58	0.2889	3.54	0.4652
	2	-13.8222	0.2299	-2.43	0.3615	3.18	0.5368

Testing for stationarity: Price graph, correlogram and Augmented Dickey-Fuller test results for OMX S30 and Electrolux.









OMX S30 DF unit root test

Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	0	0.2400	0.7408	0.22	0.7507		

Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
	1	0.2790	0.7507	0.27	0.7634		
	2	0.3082	0.7582	0.30	0.7732		
Single Mean	0	-4.0988	0.5289	-1.61	0.4794	1.79	0.6118
	1	-3.8804	0.5532	-1.57	0.4963	1.77	0.6162
	2	-3.7244	0.5710	-1.55	0.5084	1.77	0.6180
Trend	0	-6.7637	0.6837	-1.85	0.6833	1.80	0.8164
	1	-6.3164	0.7197	-1.78	0.7141	1.70	0.8380
	2	-5.9977	0.7451	-1.74	0.7355	1.62	0.8532

Electrolux DF Unit Root test

Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	0	0.7737	0.8714	0.50	0.8245		
	1	0.7742	0.8715	0.51	0.8246		
	2	0.8771	0.8919	0.60	0.8456		
Single Mean	0	-4.2600	0.5113	-1.14	0.7026	1.22	0.7593
	1	-4.2459	0.5128	-1.13	0.7045	1.21	0.7612
	2	-3.6586	0.5786	-1.02	0.7467	1.14	0.7780
Trend	0	-15.2643	0.1766	-2.58	0.2886	3.53	0.4656
	1	-15.2981	0.1755	-2.58	0.2889	3.54	0.4652
	2	-13.8222	0.2299	-2.43	0.3615	3.18	0.5368

8.4 Appendix 4 – model identification

Model selection using Bayesian Information Criterion

Minimum Information Criterion for OMX S30

Lags	MA 0	MA 1	MA 2	MA 3	MA 4	MA 5
AR 0	0.923851	0.92575	0.926272	0.926549	0.928669	0.930375
AR 1	0.925806	0.926542	0.927408	0.928509	0.930588	0.932309
AR 2	0.926346	0.927346	0.929331	0.930519	0.93263	0.933667
AR 3	0.926771	0.928619	0.930688	0.931079	0.933201	0.934789
AR 4	0.928896	0.93064	0.932741	0.933195	0.934977	0.936615
AR 5	0.930461	0.932234	0.933814	0.934811	0.93659	0.938649

Minimum Table Value: BIC(0,0) = 0.923851

Minimum Information Criterion for Electrolux

Lags	MA 0	MA 1	MA 2	MA 3	MA 4	MA 5
AR 0	1.769102	1.770525	1.76978	1.76868	1.770594	1.771868
AR 1	1.770384	1.771816	1.769917	1.770581	1.77257	1773917
AR 2	1.769444	1.769591	1.771081	1.772614	1.77461	1.775018
AR 3	1.768838	1.770671	1.772764	1.77413	1.776019	1.776657
AR 4	1.770775	1.772628	1.774735	1.775973	1.777812	1.778772
AR 5	1.771788	1.773752	1.77504	1.776666	1.778794	1.780887

Minimum Table Value: BIC(0,3) = 1.76868

8.5 Appendix 5 – Maximum Likelihood estimation in SAS

The probability density function for the multivariate ***t*** distribution is

$$P_q = \frac{\Gamma(\frac{df+m}{2})}{(\pi * df)^{\frac{m}{2}} * \Gamma(\frac{df}{2}) \, |\boldsymbol{\Sigma}(\sigma)|^{\frac{1}{2}}} * \left(1 + \frac{\mathbf{q}'(\mathbf{y}_t, \mathbf{x}_t, \boldsymbol{\theta})\boldsymbol{\Sigma}(\sigma)^{-1}\mathbf{q}(\mathbf{y}_t, \mathbf{x}_t, \boldsymbol{\theta})}{df}\right)^{-\frac{df+m}{2}}$$

where m is the number of equations and df is the degrees of freedom.

The maximum likelihood estimators of θ and σ are the $\hat{\theta}$ and $\hat{\sigma}$ that minimize the negative log-likelihood function:

$$\mathrm{l}_n(\boldsymbol{\theta}, \boldsymbol{\sigma}) = -\sum_{t=1}^{n} \ln\left(\frac{\Gamma(\frac{df+m}{2})}{(\pi * df)^{\frac{m}{2}} * \Gamma(\frac{df}{2})} * \left(1 + \frac{q_t'\boldsymbol{\Sigma}^{-1}q_t}{df}\right)^{-\frac{df+m}{2}}\right) + \frac{n}{2} * \ln(|\boldsymbol{\Sigma}|) - \sum_{t=1}^{n} \ln\left(\left|\frac{\partial q_t}{\partial \mathbf{y}_t'}\right|\right)$$

The multivariate model has a single shared degrees-of-freedom parameter, which is estimated. The degrees-of-freedom parameter can also be set to a fixed value. The log-likelihood value and the l_2 norm of the gradient of the negative log-likelihood function are shown in the estimation summary.

Since a variance term is explicitly specified by using the ERRORMODEL statement, $\boldsymbol{\Sigma}(\theta)$ is estimated as a correlation matrix and $\mathbf{q}(\mathbf{y}_t, \mathbf{x}_t, \boldsymbol{\theta})$ is normalised by the variance. The gradient of the negative log-likelihood function with respect to the degrees of freedom is

$$\frac{\partial l_n}{\partial df} = \frac{nm}{2\,df} - \frac{n}{2}\frac{\Gamma'(\frac{df+m}{2})}{\Gamma(\frac{df+m}{2})} + \frac{n}{2}\frac{\Gamma'(\frac{df}{2})}{\Gamma(\frac{df}{2})} + 0.5\log\left(1 + \frac{\mathbf{q}'\boldsymbol{\Sigma}^{-1}\mathbf{q}}{df}\right) - \frac{0.5(df+m)}{(1 + \frac{\mathbf{q}'\boldsymbol{\Sigma}^{-1}\mathbf{q}}{df})}\frac{\mathbf{q}'\boldsymbol{\Sigma}^{-1}\mathbf{q}}{df^2}$$

The gradient of the negative log-likelihood function with respect to the parameters is

$$\frac{\partial l_n}{\partial \theta_i} = \frac{0.5(df+m)}{(1 + \mathbf{q}'\boldsymbol{\Sigma}^{-1}\mathbf{q}/df)}\left[\frac{(2\,\mathbf{q}'\boldsymbol{\Sigma}^{-1}\frac{\partial \mathbf{q}}{\partial \theta_i})}{df} + \mathbf{q}'\boldsymbol{\Sigma}^{-1}\frac{\partial \boldsymbol{\Sigma}}{\partial \theta_i}\boldsymbol{\Sigma}^{-1}\mathbf{q}\right] - \frac{n}{2}\mathrm{trace}(\boldsymbol{\Sigma}^{-1}\frac{\partial \boldsymbol{\Sigma}}{\partial \theta_i})$$

where

$$\frac{\partial \boldsymbol{\Sigma}(\theta)}{\partial \theta_i} = \frac{2}{n}\sum_{t=1}^{n} \mathbf{q}(\mathbf{y}_t, \mathbf{x}_t, \boldsymbol{\theta}) \frac{\partial \mathbf{q}(\mathbf{y}_t, \mathbf{x}_t, \boldsymbol{\theta})'}{\partial \boldsymbol{\theta}_i}$$

and

$$\mathbf{q}(\mathbf{y}_t, \mathbf{x}_t, \boldsymbol{\theta}) = \frac{\varepsilon(\theta)}{\sqrt{h(\theta)}} \in R^{m \times n}$$

The estimator of the variance-covariance of $\hat{\theta}$ (COVB) for the ***t*** distribution is the inverse of the likelihood Hessian. The gradient is computed analytically, and the Hessian is computed numerically.

8.6 Appendix 6 – SAS coding for our used GARCH models

SAS Codes for GARCH modelling

Test #	Code used in SAS
Test 1	proc model data = ; parms df 7.5 arch0 .1 arch1 .2 garch1 .75 ; /* mean model */ y = intercept ; /* variance model */ h.y = arch0 + arch1 * xlag(resid.y **2, mse.y) + garch1*xlag(h.y, mse.y); /* specify error distribution */ errormodel y ~ t(h.y,df); /* fit the model */ fit y / method=marquardt fiml godfrey=3 out=resid; run; quit;
Test 2 & 6	proc model data = ; parms df 7.5 arch0 .1 arch1 .2 garch1 .75 phi -.1; /* mean model */ y = intercept ; /* variance model */ if zlag(resid.y) > 0 then h.y = arch0 + arch1*xlag(resid.y**2,mse.y) + garch1*xlag(h.y,mse.y); else h.y = arch0 + arch1*xlag(resid.y**2,mse.y) + garch1*xlag(h.y,mse.y) + phi*xlag(resid.y**2,mse.y); /* specify error distribution */ errormodel y ~ t(h.y,df); /* fit the model */ fit y / method = marquardt fiml godfrey=3 out=resid; run ; quit ;
Test 3A	proc model data = ; parms df 7.5 arch0 .5 arch1 .05 garch1 .9 rho1 .1 rho2 .1; /* mean model */ y = intercept ; /* variance model */ h.y = arch0 + arch1*xlag(resid.y**2,mse.y) + garch1*xlag(h.y,mse.y) + rho1*oi + rho2*vol; /* specify error distribution */ errormodel y ~ t(h.y,df); /* fit the model */ fit y / method = marquardt fiml godfrey=3 out=resid; run ; quit ; proc print data=resid; quit ;

Test 3B	``` parms df 7.5 arch0 .1 arch1 .2 garch1 .9 phi -.1 rho1 .5 rho2 .5; /* mean model */ y = intercept ; /* variance model */ if zlag(resid.y) > 0 then h.y = arch0 + arch1*xlag(resid.y**2,mse.y) + garch1*xlag(h.y,mse.y) + rho1*oi + rho2*vol; else h.y = arch0 + arch1*xlag(resid.y**2,mse.y) + garch1*xlag(h.y,mse.y) + phi*xlag(resid.y**2,mse.y) + rho1*oi + rho2*vol; /* specify error distribution */ errormodel y ~ t(h.y,df); /* fit the model */ fit y / method = marquardt fiml godfrey=3 out=resid; run ; quit ; ```
Test 4 & 7	``` proc model data = ; parms df 7.5 arch0 .1 arch1 .1 garch1 .85 phi -.1 delta1 .1 delta2 .1 delta3 .1 delta4 .1; /* mean model */ y = intercept ; /* variance model */ if zlag(resid.y) > 0 then h.y = arch0 + arch1*xlag(resid.y**2,mse.y) + garch1*xlag(h.y,mse.y) + delta1*unexoi + delta2*exoi + delta3*unexvol + delta4*exvol; else h.y = arch0 + arch1*xlag(resid.y**2,mse.y) + garch1*xlag(h.y,mse.y) + phi*xlag(resid.y**2,mse.y) + delta1*unexoi + delta2*exoi + delta3*unexvol + delta4*exvol; /* specify error distribution */ errormodel y ~ t(h.y,df); /* fit the model */ fit y / method = marquardt fiml godfrey=3 out=resid; run ; quit ; ```
Test 5 & 8	``` proc model data = ; parms df 17 arch0 .01 arch1 .1 garch1 .9 phi -.1 theta1 .01 theta2 .01 theta3 .01 theta4 .01; /* mean model */ y = intercept ; /* variance model */ if zlag(resid.y) > 0 then h.y = arch0 + arch1*xlag(resid.y**2,mse.y) + garch1*xlag(h.y,mse.y) + theta1*fuoi + theta2*fuvol + theta3*opoi + theta4*opvol; else h.y = arch0 + arch1*xlag(resid.y**2,mse.y) + garch1*xlag(h.y,mse.y) + phi*xlag(resid.y**2,mse.y) + theta1*fuoi + theta2*fuvol + theta3*opoi + theta4*opvol; /* specify error distribution */ errormodel y ~ t(h.y,df); /* fit the model */ fit y / method = marquardt fiml godfrey=3 out=resid; run ; quit ; ```