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Risky Relations
–
A study of the relationship between expected stock returns and volatility on the international market

Supervisor:
Professor Hossein Asgharian

Authors:
Sara Bergmark
Alexandra Cabak

Abstract

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Authors: Sara Bergmark & Alexandra Cabak

Supervisor: Professor Hossein Asgharian

This econometric study examines the relationship between expected returns and volatility in ten industrialized countries. It includes three models; GARCH-M, EGARCH-M and the PARCH-M model. Furthermore, it investigates if the results change with the use of several time intervals, different data frequency and the inclusion of macroeconomic variables into the models. The results provide evidence that no significant relationship between volatility and expected return could be identified on the international market in the long term. In the short term, a weak and unstable relationship could be found in some markets. Furthermore, the results suggest that there generally exists a positive short term relationship and a negative long term relationship between expected returns and volatility. This paper also found evidence that volatility explains the expected return in the long term in a greater extent than it does on the short term.

Keywords:
Expected stock return, volatility, GARCH-M, PARCH-M, EGARCH-M

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Term Definition

ARCH	Autoregressive Conditional Heteroscedasticity model
ARCH term	The ARCH term in the conditional variance
GARCH	Generalized Autoregressive conditional Heteroscedasticity model
GARCH term	The GARCH term in the conditional variance
GARCH-M	The GARCH in mean model
GARCH-M term	The GARCH in mean parameter
EGARCH-M	The Exponential GARCH in mean model
PARCH-M	The Power ARCH in mean model
Power term	The estimated power term in the PARCH-M model
Asymmetry term	The asymmetry term in the EGARCH-M and PARCH-M

1 Introduction

The first chapter will provide an introduction of the thesis, together with its purpose and delimitation. After the central problem discussion, a short summary of the methodology applied in this study is also included in the section together with the disposition of the paper.

1.1 Prologue

A general theory that contributes to the basis for several modern financial asset pricing models is to relate the expected return of an asset to the notion of variance. Examples are the well-known asset pricing models inter alia of Sharpe, Black and Scholes and Merton which all relates the expected return on an asset directly to its own variance or to the covariance between its return and the return on the market portfolio. Empirical evidence both corresponds and contradicts the theoretical models.

Results of previous studies indicate an inconclusiveness of the nature of the relationship between volatility and the expected return. For example Baillie and DeGennarro (1990) found only a weak and almost non-existent relationship on US stock market. Koulakiotis, Papasyriopoulos and Molyneux (2006) discovered nearly the same results; no significant relationship. In contrast to the others Glosten, Jagannathan and Runkle (1993) document a negative and significant relationship on the US market.

The contradictory nature of previous results calls for further investigation of the relationship between volatility and stock returns. Consequently, the aim of this thesis is to expand previous models and examine the relationship of expected stock return and its volatility during the period of 1990-2009 with different parametric models.

1.2 Background

Volatility and standard deviation are widely used proxies for financial risk on the stock market and numerous modern asset pricing theories assume that there is a relationship between the return of an asset and its own asset variance, or that there is a relationship between the return of an asset and its covariance with the return of the market portfolio (Sharpe 1964; Lintner 1965; Merton 1973). Nevertheless**,** several previous studies have not been able to find any significant intertemporal relationship between expected stock return and its volatility. Also the question of the positive or negative nature of the relationship is controversial. The majority of the dominating modern asset theories (Sharpe 1964; Lintner 1965; Merton 1973) assume that this relationship is of a positive and linear nature. However, some previous research indicate that this relationship is of a negative and insignificant nature (among others DeGennaro and Zhao, 1997). The relationship between return and volatility is therefore far from evident and is an important area in asset evaluation research.

A particular characteristic of financial time series of asset returns is the existence of volatility clusters. To investigate the relationship between volatility and expected return, a model is therefore needed that capture the character of the volatility clusters and allows the volatility to have different behaviour in different time intervals. As a result, to be able to forecast and analyze the volatility ARCH and GARCH models has become some of the most applied models in econometric research.

To explore the relationship between the expected return of an assets and its volatility, an extension of the GARCH model called GARCH in mean is commonly used. The GARCH-M relates the conditional variance or the standard deviation to the conditional mean of the return. Hence, it is used in financial estimations where the expected return on an asset may depend on its volatility.

Still the GARCH and GARCH-M have some limitations when it comes to modelling the volatility of asset returns, one is its inability to account for asymmetry in the chocks, a common feature of time series of assets returns meaning that negative chocks cause more volatility then positive chocks of the same magnitude, a well known feature of the volatility of asset returns. To get around this problematic limitation of the GARCH model the EGARCH model was introduced. An extension of the GARCH model that account for asymmetry in the chocks by adding a leverage coefficient into the model. Another useful model in the ARCH family is the Power ARCH model that estimates the power parameter of the standard deviation instead of assuming that it is predetermined.

1.3 Problem discussion

The results of previous studies have been conflicting regarding the relationship between expected stock returns and volatility. Using a traditional GARCH-M model Baillie and DeGennaro (1990) found only a weak and almost non-existent relationship on the U.S. stock market. Similar results were also found by Koulakiotis, Papasyriopoulos and Molyneux (2006) in a more comprehensive study were they used both a GARCH-M model and EGARCH-M model on eight countries.

In general are the results from previous studies contradictory, not only regarding the question of the existence of a significant relationship between expected returns and volatility, but also concerning the nature of this relationship. Theodossiou and Lee (1995) find a positive but insignificant relationship between the stock market volatility and expected returns in ten industrialised countries, using a GARCH-M model with logarithmic square root and linear specifications. In contrast Glosten, Jagannathan and Runkle (1993) find support for a significant negative relation between return and variance on the American market, using a GARCH-M model that allow for seasonal patterns in volatility. The results indicating a negative relationship is also in line with results from Bekeart and Wu (2000) and Whitelaw (2000).

Unlike the other studies that only focus on the intertemporal relation between returns and volatility and do not include any other economic determinants DeGennaro and Zhao (1997) include macro variables in their model to account for possible misspecifications. Their GARCH-M model therefore not only incorporates the conditional variance but also economic factors as inflation and industrial production on the American market. The results nonetheless indicate a weak, unstable and generally insignificant relationship between expected stock returns and volatility.

The importance of variance as a risk measure in stock evaluation today makes the results from previous studies quite remarkable. Despite its importance and all its appealing qualities as a risk measure much more research is thus needed before any clear consensus can emerge regarding its relevance.

The most of previous researches are done during the 90's and early 00's and do not take business cycles or macro variables into account. No previous research has either used Power ARCH to investigate the relationship between the expected returns and volatility. This study therefore expand previous studies of the relationship between expected stock returns and volatility by using not only the previously mentioned GARCH-M and EGARCH-M models, but also the PARCH-M model. To test for misspecifications macro variables will also be included in some of the models to test if that changes the results.

1.4 Problem formulation

From the problem discussion above, three questions are derived which this paper aims to answer;

I) Is there a significant relationship between expected stock returns and volatility on the international market?
   (i) Is the relationship of a positive or negative nature?

II) Which parametric model, out of GARCH-M, PARCH-M and EGARCH-M, is the most suitable to explain the relationship between expected stock return and volatility on the international stock market?
   (i) Is it possible to improve the models' ability by including macro variables into the models?
   (ii) Do the results differ between different time periods or sample intervals – with, in some cases, regards to business cycles?

1.5 Statement of purpose

The purpose of this thesis is to perform an extensive empirical econometric study of the relationship between expected stock returns and volatility on the international market using three different parametric models. Furthermore, the writers' intention is to test if the results change with the usage of several time intervals, different data frequency and by including macro variables into the models.

1.6 Method

The most previous research is done during the 90's and early 00's and do not take business cycles or macro variables into account. No previous research has either used Power ARCH to investigate the relationship between the expected returns and volatility. This study therefore expand previous studies of the relationship between expected stock returns and volatility by using not only the previously mentioned GARCH-M and EGARCH-M models, but also the PARCH-M model. To test for misspecifications macro variables will also be included in some of the models to test if that changes the results.

This study is based on a quantitative approach since it attaches importance to a large amount of data and the performance of the models. All the data is obtained from Thomson Datastream with daily and monthly frequency during 29 years. Later, the GARCH-M, EGARCH-M and PARCH-M models are applied to the data using EViews. The conclusions are based on the outcome and results from these models.

The approaches applied in this thesis is to use; several different models, different time intervals, comparison of various data frequencies and macro variables to investigate the relationship between expected stock returns and volatility on the international market. The distinguish feature of including macro variables aims to investigate if and eventually how they change the results.

Data from ten different industrialized countries are collected to investigate the relationship on the international market, these countries are: Denmark, Canada, France, USA, UK, Sweden, Japan, Italy, the Netherlands and Germany. For each country four different time periods will be chosen, first daily and monthly data of the full sample period of 29 years. Secondly, the full sample period will be divided into two sub periods, separated at half. The earlier subsamples consist of daily and monthly data, whereas the latter contains monthly data and is then extended with macro variables. Thirdly, a subsample period containing data of the years 2002 to 2009 is selected regarding the business cycle. This latter sample comprises daily and monthly data and is also extended with macro variables.

1.7 Delimitation

Any countries viewed to be emerging markets are excluded from this thesis for several reasons. An emerging market includes some problems when it comes to data gathering and estimation. Since, the classification as an emerging market automatically deals with typical problems related to that situation; occurrence of central bank and political instabilities, market anomalies and hyper inflation. Hence, obtaining data is problematical because there are often just a limited number of observations available. (OECD, oecd.org). The latter problem was faced as it first was intended to include China in this research. However, previously mentioned problems led to the decision to exclude any emerging market

1.8 Disposition

This paper's disposition proceeds as follows. The first section provides an introduction of the thesis. In section two the theoretical background will be explained. Section three will introduce the used models and section number four will present the applied methodology. The fifth section is a description of the data and the sixth section presents the results. The last section provides the analysis and conclusion of this study's examination of the relationship between expected stock returns and its volatility.

2 Model Theory

The model theory part aims to present eminent information about the models applied in the study. To test the relationship between the return on an asset and its volatility, three models – GARCH-M, Parch-M and EGARCH-M – are conducted and are explained in detail below. Hence, it is the econometric theory behind the models that is described.

2.1 Risk and volatility

Under the assumption that investors are risk averse, a higher expected return is demanded to bear more risk. In the aggregate this assumption implies that expected returns must be a function of market risk. If the risk aversion decrease as the same time as the risk increase, then higher risk will not necessarily result in a higher risk premium. But if the aggregated return changes slowly during time then higher risk also implies higher risk premium.

Many modern assets pricing models and theories assume that the variance of expected market returns is a sufficient statistic for risk, stated by for example Merton (1980). Hence, the intention of this study is to investigate the intertemporal relationship between an assets expected returns and it`s volatility, a relationship of the form:

$$E(r_t|\sigma^2) = \mu + c\sigma^2 \tag{1}$$

Were r_t is stock returns and σ^2 is the measure of the volatility of expected stock returns. If $c = 0$, this imply that there is no relation between the expected returns and the volatility. If instead $\mu = 0$ and $c > 0$ the expected return is proportionally related to the volatility.

Volatility is, as stated in the introduction, one of the most used risk measures in the financial theory, both as a measure of risk and, hence, used for deriving the price of financial assets – for instance in the Black-Scholes formula.

Since there is only a limited number of observations of the stock price a day, the volatility of a stock is not directly observable. It can only be estimated and the result will be more or less accurate, depending on the number of observations, the intraday volatility and the variation between trading days. (Tsay 2005, p. 80)

Even though asset return volatility is not directly observable it has some commonly observed characteristics. One characteristic is the existence of volatility clusters, i.e. periods of high volatility followed by periods with low volatility. Volatility also evolves in a continuous manner over time, jumps of volatility are quite rare, and does not diverge to infinity – it varies within a fixed range. It seems also to react asymmetrically to positive and negative chocks, meaning that negative chocks cause more volatility then positive chocks of the same magnitude, something also known as the leverage effect (Tsay 2005, p. 80). Financial asset returns also have the tendency to have a distribution with fat tails and excess kurtosis at the mean. (Brooks 2008)

2.2 Model structure

Volatility models are based on the idea that a series $\{r_t\}$ is dependent but not correlated, or that it only has minor serial correlations of low order. Volatility models try to capture this dependence by modelling it in different ways.

The conditional mean and conditional variance of r_t is:

$$\mu_t = E(r_t|F_{t-1}), \quad \sigma_t^2 = Var(r_t|F_{t-1}) = E((r_t - \mu_t)^2|F_{t-1}) \tag{2}$$

Were the information set is denoted by F_{t-1} and include all available information, in general, linear functions of past returns. Modelling conditional heteroscedasticity is therefore fundamentally to adapt a dynamic equation to a time series model to capture how the conditional variance of the chock develops over time. (Tsay 2005, p.82)

In the empirical study the conditional mean and variance will be estimated jointly. However, in this theoretical chapter the model for the conditional mean will, for simplicity, be assumed to be following:

$$r_t = \mu_t + a_t, \tag{3}$$

The following section contains a description of the all the models related to this research paper.

2.3 Symmetric models

The different models in the ARCH family are divided into two groups – symmetric and asymmetric models. Symmetric models emphasize the magnitude of chocks. Thus, it is not the positive or negative nature of the chocks that determine the conditional variance σ_t^2, but the magnitude of these chocks. (Xekalaki 2010) Models from both subsets will be applied in this thesis to investigate any difference in the outcome of the results.

The following section contains a description of the symmetric models related to this research paper. Two of the three models described below are underlying models that are important and simplifies the understanding of the other models explained in this chapter. The two underlying models, the ARCH and the GARCH models, are therefore described due to their fundamental assumptions but are not going to be applied on data in this thesis. The third symmetric model, GARCH-M, is explained and will be used in this research.

2.3.1 The ARCH model

Engle (1982) was the first to introduce the concept of conditional heteroscedasticity and to provide a systematic framework for volatility modelling. His Autoregressive conditional heteroscedastic, ARCH, model is based on the idea that the dependence of the asset can be modelled by a quadratic function of its lagged values. (Harris & Solis 2010, p. 213) The ARCH (m) model can be written:

$$a_t = \sigma_t \epsilon_t, \quad \sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \cdots + \alpha_m a_{t-m}^2 \qquad (4)$$

Where $\alpha_0 > 0$ and $\alpha_i \geq 0$ for $i > 0$ and $\{\epsilon_t\}$ is a sequence of random variables that is independent identically distributed (IID) variables with mean 0 and variance 1.0, often assumed to have a normal distribution or a standardized t-distribution.

Because the structure of the model imply that large shocks tend to be followed by other large shocks the model captures the behaviour of volatility clustering that is typical for financial time series (Tsay 2005, p. 83). A weakness of the model is**,** though**,** that to describe the volatility process of asset returns adequately, it often requires many parameters and can be complicated to use (Tsay 2005p. 93). Based on these parameter drawbacks of the ARCH model, Bollerslev and Taylor (1986) independently developed a useful extension that they titled; Generalized Autoregressive Conditionally Heteroscedastic model, or GARCH (Harris & Solis 2003, p. 213).

2.3.2 The GARCH model

Both ARCH and GARCH models are constructed to manage volatility clustering but in contrast to the ARCH model, the GARCH model includes lags of the conditional variance as regressors' in the conditional variance (Harries and Solis 2003, p. 220). A GARCH (m, s) model has the equation as below:

$$a_t = \sigma_t \epsilon_t, \qquad \sigma_t^2 = \alpha_0 + \sum_{j=1}^{m} \alpha_j a_{t-j}^2 + \sum_{i=1}^{s} \beta_i \sigma_{t-i}^2 \tag{5}$$

Where $0 \leq \alpha_i,\ \beta_i \leq 1$ and $(\alpha_i + \beta_i) < 1$ where the latter implies that the unconditional variance of a_t is finite, while the conditional variance σ_t^2 evolves over time. The sequence of random variables $\{\epsilon_t\}$ is independent identically distributed (IID) with mean 0 and variance 1.0, and is often assumed to have a normal distribution or a standardized t-distribution. The conditional variance includes: The constant term α_0, the ARCH term a_{t-j}^2, which includes the news about the volatility from past periods, and the GARCH term σ_{t-i}^2, which is the last periods variance. (Tsay 2005,p. 93)

2.3.3 The GARCH-M model

The GARCH in mean, GARCH-M, is an extension of the GARCH model and is often used for financial estimations where the expected return on an asset may depend on its volatility. The extension is developed by relating the conditional variance or the conditional standard deviation to the conditional mean of returns, a GARCH (m,s)-M model can be written as:

$$r_t = \mu + c\sigma_t^2 + a_t, \quad a_t = \sigma_t \epsilon_t$$

$$\sigma_t^2 = \alpha_0 + \sum_{j=1}^{m} \alpha_j a_{t-j}^2 + \sum_{i=1}^{s} \beta_i \sigma_{t-i}^2 \tag{6}$$

Where μ and c are constant and c is the risk premium parameter. If the risk premium parameter is positive, that indicates that the return of the asset is positively related to its past volatility (Tsay 2005 p. 101).

There are some drawbacks with the GARCH-M model. The first and main disadvantage with this model, observed by Nelson (1991), is the choice of the quadratic form which implies that only the magnitude of a shock's past values has an impact on the current volatility. A feature that generally is incorrect because volatility of financial time series tend to became higher after a decline than after an equal increase according to Campbell and Hentschel (1990). A second disadvantage with the model is the non-negativity of the parameters, because regardless the sign of the shock, a shock always have a positive impact on the current volatility. I.e. the volatility always increases with the magnitude of the shock. A logical conclusion is then that the model is not able to take cyclical or any non-linear behaviour into account in the volatility.

2.4 Asymmetric models

Previous studies by Christie (1982) and Black (1976) imply that when the equity value of a firm decrease**,** the risk of a firm will increase due to the augment of debt in the capital structure. This implies that a negative chock can increase the volatility more than positive chocks of the same magnitude (Black 1976). The second subset of the ARCH-family is therefore the asymmetric models. In contrast to the symmetric models, the asymmetric ones take the positive and negative nature of the chocks into account.

Hence, the conditional variance depends also on the sign of the error term and not only of the magnitude of the chock (Xekalaki 2010 p.42). The two applied asymmetric models in this research are the EGARCH and the PARCH Model.

2.4.1 The EGARCH-M model

EGARCH is another model in the ARCH family and is an abbreviation of Exponentially GARCH. The model was introduced by Nelson in 1991 with the intention of getting around the problematic limitations of the GARCH and GARCH-M model by adding a leverage coefficient into the model, a leverage coefficient that gives the model the ability to manage the asymmetric features of the chocks. An EGARCH model can be written as:

$$a_t = \sigma_t \epsilon_t, \quad ln(\sigma_t^2) = \alpha_0 + \sum_j^m \beta_j log(\sigma_{t-j}^2) + \sum_i^s \alpha_i \left| \frac{a_t - i}{\sigma_{t-i}} \right| + \sum_k^r \gamma_k \frac{a_{t-k}}{\sigma_{t-k}} \qquad (7)$$

Where the presence of asymmetry in response to positive and negative chocks can be tested with the hypothesis that $\gamma_k = 0$ and there is asymmetry if $\gamma_k \neq 0$.

An extension of the EGARCH model is the EGARCH in mean.
The EGARCH-M (m, s) model can be written as:

$$a_t = \sigma_t \epsilon_t, \qquad r_t = \mu + c\sigma_t^2 + a_t, \;\; a_t = \sigma_t \epsilon_t$$

$$ln(\sigma_t^2) = \alpha_0 + \sum_j^m \beta_j log(\sigma_{t-j}^2) + \sum_i^s \alpha_i \left| \frac{a_t - i}{\sigma_{t-i}} \right| + \sum_k^r \gamma_k \frac{a_{t-k}}{\sigma_{t-k}} \tag{8}$$

The EGARCH model secures the conditional variance to be positive even if the parameters are negative, since the conditional variance is modelled in logarithmic form. (Tsay 2005, p. 102-103)

2.4.2 The PARCH-M model

The standard Power ARCH, PARCH, was introduced by Ding, Granger and Engle (1993) and is a generalized version of the standard deviation GARCH by Taylor (1986) and Schwert (1989). In the PARCH model, the power parameter of the standard deviation, δ, is estimated instead of being imposed, a way of getting around the drawbacks with the GARCH-M model that were mentioned earlier in sub section 3.2.3.

Parameter γ_i accounts for the leverage effect and there is asymmetry in the chocks if $\gamma_i \neq 0$. A PARCH in mean model with asymmetry up to order r can be written:

$$r_t = \mu + c\sigma_t^2 + a_t, \;\; a_t = \sigma_t \epsilon_t$$

$$\sigma_t^\delta = \alpha_0 + \sum_{j=1}^q \beta_j \sigma_{t-j}^\delta + \sum_{i=1}^p \alpha_i (|a_{t-i}| - \gamma_i a_{t-i})^\delta \tag{9}$$

$\delta > 0$, $|\gamma_i| > 1$ for i=1,…….,r, $\gamma_i = 0$ for all $i > r$, and $r \leq p$.
As it can be noticed the model turn into a standard GARCH if $\gamma_i = 0$ and $\delta = 2$.

2.4.3 The null hypothesis

The null hypothesises for all three models are:

$$H_0: c = 0 \qquad\qquad H_1: c \neq 0$$

Hence, if the null hypothesis cannot be rejected at the five percent significance level, there is no support for any relationship between stock price returns and volatility, the relationship is said to be insignificant. If there is a support for the alternative hypothesis, it cannot be excluded that there exist a relationship between expected stock returns and volatility.

3 Methodology

The aim of this chapter is to present a proper description of the methodology used for this thesis. Thus, this section will consist of a extended explanation of the models used and ends with a description of the reliability and validity of this research.

3.1 Macroeconomic variables

In a study of the relationship between expected stock returns and volatility, DeGennaro and Zhao (1997) expand their GARCH-M model with macroeconomic variables in both the mean equation and the conditional variance. The reason for this expansion is to test whether the difficulty of identifying a significant relationship between expected stock returns and volatility in previous studies depends on model misspecifications that bias the results.

In this study the same approach is applied with the intention of testing if the inclusion of macroeconomic variables improves the models and thus changes the results. As in the study done by DeGennaro and Zhao, macroeconomic variables are first included in the mean equation and then both in the mean equation and the conditional variance.

3.2 Model specification

The study will mainly be based on three different models: A basic GARCH-M model, an EGARCH-M model and finally a PARCH-M. PARCH-M is a new approach, in the sense of that no research has applied the model before to test the relationship between expected stock return and volatility.

3.2.1 GARCH in mean

The first model is a GARCH-M model that assumes a linear relation between volatility and return. The model is written as follows:

$$r_t = \mu + c\sigma_t^2 + a_t, \quad a_t = \sigma_t \epsilon_t$$
$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{10}$$

Were $\alpha_0$is a constant and c is the slope coefficient of the conditional variance.

3.2.2 EGARCH in mean

The second model is an EGARCH-M model that allows for asymmetry in the conditional variances and permits the stock price returns to respond asymmetrically to bad and good news. The model is written as follows:

$$r_t = \mu + c\sigma_t^2 + a_t, \quad a_t = \sigma_t \epsilon_t$$
$$a_t = \sigma_t \epsilon_t, \quad ln(\sigma_t^2) = \alpha_0 + \beta_1 log(\sigma_{t-1}^2) + \alpha_1 \left|\frac{a_t - 1}{\sigma_{t-1}}\right| + \gamma \frac{a_{t-1}}{\sigma_{t-1}} \tag{11}$$

3.2.3 PARCH in mean

The third model is a PARCH-M model. In this model the power parameter of the standard deviation is estimated instead of being imposed as it is in the standard GARCH. The model is written as follows:

$$r_t = \mu + c\sigma_t^2 + a_t, \quad a_t = \sigma_t \epsilon_t$$
$$\sigma_t^\delta = \alpha_0 + \beta_1 \sigma_{t-1}^\delta + \alpha_i (|a_{t-1}| - \gamma a_{t-1})^\delta \tag{12}$$

3.2.4 Macroeconomic variables in the mean equation

Some of the models are also expanded with macroeconomic variables V_i, in the mean equation. A further description of the economic variables can be found in chapter three.

3.2.5 Macroeconomic variables in the mean equation and in the conditional variance

In the fourth model the macroeconomic variables V_i, are not only included in the specification of the expected return but also in the conditional variance.

3.3 Model estimation

All models are estimated in EViews using the method of maximum likelihood. Maximum likelihood requires an assumption of the distribution of the error terms and since financial time series frequently have fat tails a student t-distribution are assumed.

Because of the nonlinearity of the variance, the likelihood function is estimated using iterative algorithms, an iterative process that will continue until the estimates converge. The quality of the estimates depends on how good the starting values are. If the starting values are far from the real values the convergence achieved can be a local maximum and the quality of the estimate will be poor.

To estimate the initial variance, which is needed to compute the GARCH terms, EViews use a method called backcasting. Backcasting is a backward recursion method that is used to estimate the residuals of the mean equation by using the values of the coefficients. An exponential smoothing estimator is then computed of the initial values. This parameter can be adjusted, but we will use the already preset smoothing parameter 0.7.

In the GARCH in mean, the EGARCH in mean and the PARCH in mean, the conditional variance or conditional standard deviation is included in the mean equation. DeGennaro and Zhao (1997) conclude that the quality of the model improves if the conditional variance is used in instead of the conditional standard deviation, we will therefore follow their recommendation and use the conditional variance instead of the conditional standard deviation.

3.4 Model evaluation approach

All the models, GARCH-M, EGARCH-M and PARCH-M will be used on both the daily and the monthly data from both the full sample period, and all the three sub sample periods. But not all models will be expanded with macroeconomic variables. For a graphical overview please see table 4.1 below.

Table 4.1 – Model Estimation Approach

Sample	Interval	Frequency	Model	∑ tests
Full period	1980-2009	Daily Monthly	GARCH-M PARCH-M EGARCH-M	54
First subperiod	1980-1993	Daily Monthly	GARCH-M PARCH-M EGARCH-M	54
Second subperiod	1994-2009	Monthly Daily	GARCH-M PARCH-M EGARCH-M	90
		Monthly	EGARCH-M + Macroec. Variables set one EGARCH-M + Macroec. Variables set two	
Fourth period	2002-2008	Daily Monthly	GARCH-M PARCH-M EGARCH-M	90
		Monthly	EGARCH-M + Macroec. Variables set one EGARCH-M + Macroec. Variables set two	
				∑=288

All the models will first be estimated without the macroeconomic variables and then be evaluated. The decision of which model to expand is based on the results of the evaluation. If all three models are suitable, then the macroeconomic variables will be included in all three models. If one of the models do not seems to be appropriate for the inclusion of macro variables, it will not be expanded.

3.5 Diagnostic tests

To evaluate the robustness of the models some diagnostic tests will be performed on each model. The specification of the mean equation will be tested using a correlogram of the standardized residuals, to check for remaining autocorrelation in the residuals. Also, the specification of the variance equation will be tested using an ARCH LM test and a correlogram of the squared residuals, controlling if there is any remaining autoregressive conditional heteroscedasticity, ARCH effects, in the residuals. The Jarque-Bera statistic will also be used to test if the standardized residuals are normally distributed.

3.6 Reliability and validity

To measure the reliability and validity of this thesis, the theoretical and methodological approach has been evaluated. The reliability of the data is discussable since the source of the raw data used is Thomson Datastream, which provide secondary data. Thus, it is secondary data and allows for imperfections. However, Datastream is a commonly used data source among academics and researcher.

The methodological approach follows previous researches to an extent level, but still there has to be made some individual assumptions when estimating the volatility using the models in the ARCH-family – for example the starting values. The reliability of this research is found overall high, but when it comes to the specifications of the models it faces some drawbacks. I.e. there is a risk that this paper reaches a local maximum instead of the global maximum that is strived after, because of using the likelihood function. Hence, assuming same data, it may be that another researcher find another optimum and consequently get other results when estimating the volatility with likelihood function. However, this may not be to an extent that influences the significance of the outcome results. Due to the use of empirical well applied econometric models, the modelling part is transparent and should in itself be reliable.

The validity of this thesis is fulfilled thus the variables are selected among course literature and previous researches. However, the econometric models chosen are used in similar previous researches and are also overall commonly used in econometrics.

4 Data

In the following data chapter, a distinguished discussion and explanation of how the data is gathered and processed is presented. There is also a section including motivation of which data frequency that will be used and why.

Ten industrialized countries were selected to be the foundation of the international perspective of this research. The industrialized countries were Canada, Denmark, France, Germany, Netherlands, Italy, Japan, Sweden, UK and USA. Due to their membership of the Group-of-Ten, G10, countries they are suitable as an instrument to measure the relationship between the volatility and the return on stock return, due to their well-traded indices (OECD, oecd.com).

4.1 Return estimation and distribution

The stock returns are estimated by using basic series of daily and monthly data of the Morgan Stanley Capital Index gathered in Datastream – table 5.1 below indicates a summary of all countries and their indices:

Table 5.1

Country	Index
Canada	MSCNDAL
Denmark	MSDNMKL
France	MSFRNCL
Germany	MSGERML
Italy	MSITALL
Japan	MSJPANL
Netherlands	MSNETHL
Sweden	MSSWDNL
UK	MSUTDKL
US	MSUSAML

To investigate the behaviour of the returns, the distribution for daily returns were evaluated for each country, see appendix A1.

The distribution shows the behaviour of returns calculated with the following formula:

$$r_t = \ln(P_t/P_{t-1}) \quad (13)$$

Were P_t, is the stock price today and P_{t-1} is the stock price yesterday. The estimated return above is also known as the continuously compounded returns, or simply; log returns. The use of log returns is beneficial since the statistical properties are more suitable.

According to the graph displayed in appendix A1, describing the distribution of the log returns, all countries are negatively skewed except Sweden. Further, the kurtosis reaches a value between 7 and 25 for seven countries. Hence, the log return of the countries are said to be leptokurtic, since they have a kurtosis larger than three – which should be the value if the data is normal distributed. This is also indicated by the high, acute top and the fat tails. Thus, the probability of extreme outcomes is higher. According to the Jarque-Bera test of normality is the null hypothesis of normally distributed log returns rejected for all countries on the 10%, 5% and 1% significance level

4.2 Subsample selection

Data from the ten countries are obtained in different data frequencies and different time periods. First, are data from all indices collected for the interval of 30 years, i.e. January 1980 to December 2009. Due to the aim of reliable empirical results, both a daily and a monthly frequency of the data are chosen.

A purpose of this paper is to see if there is a difference of the results using different data frequencies and also dividing the sample into more subsamples with a shorter interval than 30 years. Hence the full samples, both daily and monthly data, are divided into two subsamples, January 1980 to December 1993 and January 1994 to December 2009. All the models are then used on both of the two sub sample periods.

In addition to the large data sample intervals of 30 and 15 years, a smaller sub sample period is also chosen to investigate the relationship between expected stock returns and volatility during a short and economically growing period. The last subsample will therefore consist of data from January 2002 to December 2008, a time period of economic boom that not include the economically turbulent year of 2009.

The stock price indices are obtained in local currency and in contrast to extant literature no missing values exists in this research. The price indices do not contain dividends.[1] Hence, total number of daily return observations per country is 7 868.

In appendix A1 the logarithmic returns for each country are graphed, the graph indicates present volatility clustering in the obtained data set of the individual stock price indices.

4.3 Selection of macro variables

Two different set of macro variables are used in the models to investigate if affect the results. The basic series of the monthly data for all the macroeconomic variables are collected from DataStream. Because these are typically reported monthly, macroeconomic variables are only used in the models based on monthly data. The intention was to first evaluate all the models without macro variables and then expand the model that seemed to be the most appropriate. But due to lack of data in the 80's only models in the second and third sub period are expanded with macro variables.

The different explanatory variables are selected on the basis of previous empirical research. The first set of macroeconomic variables, are the variables that were used by DeGennaro and Zhao (1997). These are: Industrial production, inflation and term structure. The used variables are calculated as follows;

- The industrial production is the change in the log of the monthly total industrial production index for every country:

$$IP(t) = \log\big(IPI(t)\big) - \log(IPI(t-1)) \quad (14)$$

- Inflation is calculated in a similar way, as the first difference of the log of the Consumer price index for each country:

$$CPI = \log\big(CPI(t)\big) - \log(CPI(t-1)) \quad (15)$$

[1] Nelson (1991) found that there is "virtually no difference in either the estimated parameters or the fitted variance" when two EGARCH-M models were tested; one with dividends, one without dividends.

- The term spread is the difference between 10 years Government Bond Yield and the rate of three months treasury bills:

$$TS = \left(\log\left(GB10(t)\right) - \log\left(GB10(t-1)\right)\right) - \left(\log\left(TS(t)\right) - \log\left(TS(t-1)\right)\right) \quad (16)$$

A second set of macro variables are also used. These variables are from an article of Rapach, Wohar and Rangvid (2005) that investigate the predictability of stock returns using macroeconomic variables in twelve industrialized countries. These variables are chosen by Rapach, Wohar and Rangvid because they are commonly used in the empirical literature to predict and explain stock returns, which is also the reason to why we found it interesting to include them in our model. The macro variables that are: three months Treasury bill rate, long term government bond yield, term spread, inflation rate, money growth and unemployment rate. The variables are defined in the following way:

- The money growth is the change in the log of the narrowly defined money stock in each country:

$$MS = \log\left(MS(t)\right) - \log(MS(t-1)) \quad (17)$$

- The unemployment rate is calculated in the same way:

$$UR = \log\left(UR(t)\right) - \log(UR(t-1)) \quad (18)$$

The calculations of the three months Treasury bill rate, the long term government bond yield, the term spread and the inflation rate are calculated as described earlier.

5 Empirical results

This part presents a discussion of the results from the empirical application in the latter chapter. Providing and understanding of the results and basis for the coming analysis in the next chapter. Appendix A2 to A4 reports tables of the empirical application. Due to lack of space, all the 288 tests cannot be included in the appendix – these can be provided on request.

5.1 Full sample period – 1980-2009

All the models, i.e. GARCH-M, EGARCH-M and PARCH-M, were used both with daily and monthly data from the full sample period. The results using daily and monthly data are in this chapter evaluated separately and are graphed in appendix chapter A2.

5.1.1 Daily data

The results of the full sample period with daily data are summarized in table 6.1 on the following page and the diagnostic test results are presented in appendix A2.1.

Using the GARCH-M model with daily data, all the ARCH and GARCH terms are clearly significant. Furthermore, the size of the coefficients suggests that the current volatility is more affected by the volatility of past returns then by chocks in the last period. The intercepts of the mean equations are positive and significant but very small. Additionally, the GARCH-M terms are positive for all countries except Sweden, but insignificant. Hence, the results imply a positive but insignificant relation between expected stock returns and volatility in the majority of the countries.

However, the diagnostic tests indicate signs of autocorrelation in the standardized residuals in almost all countries. An indication of that the mean equation could be wrongly specified. The squared residuals also imply that there are remaining ARCH effects in the standardized residuals of Canada and UK. This could result in a loss of efficiency and suggest a wrongly specified variance equation. The null of normally distributed residuals are clearly rejected.

Table 6.1

GARCH-M, PARCH and EGARCH-M Estimations
daily data 1980-2009

Coefficient	CA	DK	FR	GM	IT	JP	NL	SE	UK	US
GARCH-M										
Intercept	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
p-value	0,00	0,00	0,00	0,00	0,05	0,00	0,00	0,00	0,00	0,00
garch-m	2,07	0,39	0,47	1,39	2,13	1,20	0,03	-0,24	0,77	1,49
p-value	0,12	0,78	0,71	0,21	0,06	0,27	0,98	0,82	0,62	0,27
arch*	0,07	0,09	0,08	0,08	0,08	0,09	0,09	0,09	0,07	0,05
	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
garch	0,92	0,90	0,90	0,91	0,82	0,91	0,93	0,91	0,96	0,94
p-value	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
EGARCH-M										
intercept	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
p-value	0,00	0,00	0,00	0,00	0,06	0,00	0,00	0,00	0,00	0,04
garch-m	1,67	-1,29	-0,19	0,97	1,53	0,23	-0,35	-1,06	0,95	2,14
p-value	0,22	0,35	0,88	0,38	0,17	0,84	0,77	0,31	0,55	0,12
arch*	0,13	0,17	0,15	0,15	0,17	0,18	0,16	0,17	0,14	0,10
p-value	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
garch*	0,99	0,98	0,98	0,99	0,98	0,98	0,99	0,99	0,98	0,99
p-value	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
asymetri*	-0,03	-0,03	-0,06	-0,05	-0,04	-0,75	-0,05	-0,04	-0,05	-0,07
p-value	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
PARCH-M										
intercept	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
p-value	0,00	0,00	0,00	0,00	0,03	0,02	0,00	0,00	0,00	0,01
garch-m	1,45	-1,41	-0,36	0,56	1,10	-0,56	-0,50	-1,12	0,41	1,30
p-value	0,28	0,30	0,77	0,61	0,32	0,61	0,66	0,28	0,79	0,32
arch*	0,07	0,10	0,08	0,08	0,09	0,07	0,08	0,09	0,07	0,06
p-value	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
asymetri*	0,15	0,16	0,35	0,30	0,19	0,61	0,26	0,19	0,25	0,62
p-value	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
garch*	0,93	0,91	0,91	0,92	0,91	0,06	0,92	0,91	0,92	0,95
p-value	0,00	0,00	0,00	0,00	0,00	0,01	0,00	0,00	0,00	0,00
power*	1,62	1,17	1,46	1,30	1,40	-0,03	1,48	1,54	1,71	1,15
p-value	0,00	0,00	0,00	0,00	0,00	0,25	0,00	0,00	0,00	0,00

* = normal distribution
CA = Canada, DK = Denmark, FR = France, GM = Germany, IT = Italy, JP = Japan, NL = Netherlands, SE = Sweden, UK = United Kingdom, US = United States

Using the EGARCH-M model and the PARCH-M model, the GARCH-M term is negative for Denmark, France, the Netherlands and Sweden but always insignificant. With the PARCH-M model also the GARCH-M term for Japan becomes negative. Otherwise, are the results of the EGARCH-M and PARCH-M models generally similar to the results of the GARCH-M model.

There are indications of autocorrelation in the standardized residuals for all countries and there are signs of remaining ARCH effects in the squared residuals of Canada and UK. The null hypothesis of normally distributed residuals is clearly rejected for all countries.

The asymmetric term of the PARCH-M model is significant for all countries and the same occurs with the asymmetric term of the EGARCH-M model, which also is clearly negative, implying that there is negative asymmetry in the chocks. It is also notable that the power term of the PARCH-M model is between one and two and is significant for all countries except for Japan, which has a negative and insignificant power term.

5.1.2 Monthly data

The results from the full sample period with monthly data are summarized in table 6.2 below and the diagnostic test results are presented in appendix A2.2.

Table 6.2
GARCH-M, PARCH and EGARCH-M Estimations
monthly data 1980-2009

Coefficient	CA	DK	FR	GM	IT	JP	NL	SE	UK	US
GARCH-M										
intercept	0,01	0,00	0,01	0,01	0,00	0,01	0,01	0,02	0,01	0,01
p-value	0,00	0,61	0,00	0,04	0,59	0,37	0,06	0,06	0,09	0,28
garch-m	0,63	0,57	1,57	-0,68	0,57	-0,62	-0,98	-0,09	1,38	0,37
p-value	0,74	0,64	0,44	0,67	0,74	0,81	0,70	0,96	0,53	0,30
arch*	0,13	0,15	0,17	0,19	0,14	0,11	0,29	0,17	0,16	0,33
p-value	0,02	0,01	0,05	0,03	0,01	0,04	0,03	0,02	0,04	0,00
Garch	0,l76	0,75	0,68	0,72	0,80	0,79	0,24	0,70	0,73	0,67
p-value	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
EGARCH-M										
intercept	0,00	0,05	0,01	0,02	0,01	0,02	0,01	0,03	0,01	-0,01
p-value	0,04	0,01	0,12	0,04	0,39	0,02	0,12	0,06	0,21	0,96
garch-m	-0,44	-13,39	-0,16	-3,52	-0,27	-5,26	-0,50	-3,27	2,12	0,45
p-value	0,83	0,06	0,94	0,25	0,89	0,07	0,84	0,17	0,36	0,24
arch*	0,23	0,12	0,30	0,36	0,31	0,17	0,35	0,27	0,25	0,38
p-value	0,02	0,06	0,03	0,02	0,00	0,06	0,01	0,01	0,05	0,00
asymetri*	-0,11	-0,10	-0,17	-0,13	-0,00	-0,23	-0,15	-0,13	-0,07	-0,25
p-value	0,03	0,03	0,01	0,15	0,88	0,00	0,04	0,04	0,34	0,00
garch*	-0,85	0,81	0,77	0,06	0,90	0,72	0,62	0,79	0,85	0,92
p-value	0,00	0,00	0,00	0,80	0,00	0,00	0,00	0,00	0,00	0,00
PARCH-M										
intercept	0,01	0,01	0,01	0,01	0,00	0,02	0,01	0,03	0,00	-0,01
p-value	0,03	0,10	0,16	0,04	0,65	0,03	0,04	0,01	0,45	0,75
garch-m	-0,59	-1,75	0,33	-0,76	0,61	-4,73	-1,75	-3,76	3,14	0,37
p-value	0,76	0,49	0,85	0,64	0,77	0,10	0,46	0,14	0,17	0,31
arch*	0,10	0,22	0,18	0,19	0,17	0,11	0,22	0,13	0,13	0,18
p-value	0,33	0,00	0,01	0,04	0,00	0,00	0,00	0,17	0,06	0,00
asymetri*	0,47	0,64	0,70	0,04	-0,01	1,00	0,65	0,36	0,66	0,82
p-value	0,28	0,06	0,00	0,82	0,91	0,00	0,00	0,09	0,09	0,00
garch*	0,67	0,45	0,61	0,72	0,76	0,68	0,49	0,57	0,69	0,79
p-value	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
power*	2,08	0,66	0,58	1,85	1,44	0,83	0,76	2,39	0,55	1,25
p-value	0,10	0,05	0,23	0,08	0,03	0,06	0,03	0,11	0,37	0,00

* = Normal distribution
CA = Canada, DK = Denmark, FR = France, GM = Germany, IT = Italy, JP = Japan, NL = Netherlands, SE = Sweden, UK = United Kingdom, US = United States

With monthly data, the GARCH terms and the ARCH terms are significant in most cases, regardless of model. The size of their coefficients also suggests, as with the daily frequency, that the current volatility is more affected by the volatility of past returns then by chocks in the returns in the last period.

Using the GARCH-M model, the GARCH-M term is negative for Germany, Japan, the Netherlands and Sweden but never significant. The intercepts are positive and greater than with daily data but only significant for Canada, France and Germany. The results are similar for the PARCH-M model, with the difference that using this model also the GARCH-M term for Canada and Denmark are negative. The intercept of the mean equations are negative for the U.S and significant for Canada, Germany, Japan, the Netherlands and Sweden.

With the EGARCH-M model, all the GARCH-M terms are negative for all countries except for UK and the U.S. The GARCH-M terms are insignificant for all countries except in Denmark were it is almost significant on the five percent level. The intercept is, on the contrary, positive for most countries except the U.S. but only significant for Canada, Denmark, Germany and Japan. This allows for the interpretation of a negative but insignificant relationship between expected return and volatility.

The asymmetry term of the PARCH-M model is only significant for France, Japan, the Netherlands and the U.S. In contrast, the asymmetric term of the EGARCH-M model is always negative and significant for the majority of the countries. Hence, indicating asymmetry in the chocks. The value of the PARCH-M power term has a value between 0.5 and 2.4 and is significant only for Italy and the U.S.

The results of the diagnostic tests differ from those with daily frequency. Using monthly data, most of the autocorrelation is eliminated, regardless of model. Only for Italy there are still some signs of autocorrelation, despite model. There are neither any signs of remaining ARCH effects in any of the models. Using the EGARCH-M model and the PARCH-M model the residuals seems to approach a normal distribution, but the null hypothesis of normal distribution is still rejected on the one percent level in most of the cases.

5.2 Subsample periods – 1980-1993 and 1994-2009

By dividing the full sample into two, two equal subsamples were generated. All the models are then, as with the full sample period, applied on both daily and monthly data. The best performing model were then expanded with macro variables to test if the insignificance of the GARCH-M term were caused by misspecifications of the mean and/or the conditional variance equation. Due to difficulty to find macroeconomic data for the earlier time period

1980-1993, for the majority of the countries, only the models used on monthly data from the second sub period were expanded with macroeconomic variables. Since the main purpose of adding macro variables to the models were to improve the models to see if the results changed and not to analyse the individual characteristics of the macroeconomic variables no detailed analysis will be preformed regarding these variables. All results are presented in tables in appendix chapter A3.

5.2.1 Daily data

Overall, splitting the full sample period into two sub samples does not change the results remarkably, looking at each sub period separately. However, some interesting features can be noticed in the two time periods. The main findings are summarized in table 6.3 below, for more detailed results and diagnostic tests see appendix A3.1 – A3.2.

Not only is the GARCH-M term insignificant regardless of which model that is used, but also the sign of the term seems to be quite unstable, changing from one sub period to another. In both periods is the majority of the intercepts of the mean equation positive and significant.

Table 6.3
Significant Intercept and GARCH-M Term in all models
GARCH-M, PARCH and EGARCH-M Estimations , Daily data, 1980-1993 and 1994-2009

coefficient	CN	DK	FR	GM	IT	JP	NL	SE	UK	US
Subsample 1980-1993										
GARCH-M										
intercept	0,000	0,000	0,001*	0,000	0,000	0,000*	0,001***	0,001***	0,001***	OF
garch-m	2,781	-0,262	0,106	2,204	3,409	1,925	-1,482	1,393	-0,971	
EGARCH-M										
intercept	0,000	0,001*	0,001***	0,000	0,000	0,000**	0,001***	0,001***	0,001**	0,000
garch-m	2,68	-0,618	-1,797	2,302	3,553	-0,022	-1,508	0,734	-2,651	5,69
PARCH-M										
intercept	0,000	0,001*	0,001***	0,000	0,000	0,000*	0,001***	0,001***	0,001**	OF
garch-m	2,397	-0,91	-2,026	1,498	2,87	-0,686	-1,625	0,409	-1,939	
Subsample 1994-2009										
GARCH-M										
Intercept	0,001***	0,001***	0,001*	0,001**	0,000	0,000	0,001**	0,001***	0,00*	0,001***
garch-m	0,841	-0,686	0,810	0,727	1,385	1,848	0,614	-1,083	1,718	0,967
EGARCH-M										
intercept	0,001***	0,001***	0,000	0,00*	0,000	0,000	0,00**	0,001***	0,000	0,00*
garch-m	0,631	-1,233	0,913	0,581	0,875	2,337	-0,168	-1,458	2,104	1,395
PARCH-M										
intercept	0,001***	0,001***	0,000	0,00*	0,000	0,000	0,00*	0,001***	0,000	0,00**
garch-m	0,341	-1,340	0,664	0,354	0,302	1,123	-0,297	-1,347	1,518	0,658

* Significance p<5% ** Significance p<1% ***Singificance p<0,1% OF=Overflow, no convergence of the model.

CA = Canada, DK = Denmark, FR = France, GM = Germany, IT = Italy, JP = Japan, NL = Netherlands, SE = Sweden, UK = United Kingdom, US = United States,

5.2.2 Monthly data

As previously, the results of the sub sample periods are quite similar to the results of the full sample period. An important exception is, though, that the standardize residuals appears to approach a normal distribution and the null hypothesis of normally distributed residuals cannot be rejected for five out of nine countries in the second sub sample period, using the EGARCH-M model. With the same model are also for the first time, the ARCH and the GARCH term insignificant in the first sub sample period, 1980-1993.

The GARCH-M term is significant only once in each sub sample period, as can be noted in below table 6.4, both times using the EGARCH-M model. It is also interesting to note that the majority of the intercepts of the mean equation are insignificant, in contrast to when daily data were used and the intercepts were mostly significant. The sign of the GARCH-M term is also in a greater extent negative with monthly data compared to with data of daily frequency. The further, with monthly data the sign of the GARCH-M term seems to be less unstable then with daily data. This observation is especially evident when observing the result of the EGARCH-M model, were the majority of the countries has the same sign in both time periods. For more detailed results, see appendix A3.3 to A3.4

Table 6.4
Significant Intercept and GARCH-Term
GARCH-M, PARCH and EGARCH-M Estimations, Monthly data, 1980-1993 and 1994-2009

coefficient	CN	DK	FR	GM	IT	JP	NL	SE	UK	US
Subsample 1980-1993										
GARCH-M										
intercept	-0,032		0,014			0,011			0,004	-0,017
garch-m	14,712	OF	-0,079	OF	OF	-0,152	OF	OF	4,486	-1,121
EGARCH-M										
intercept	-0,005	-0,578	0,112	0,027	-1,494	0,012	0,014	0,544	-0,017	-0,033**
garch-m	-4,59	-2,494	-27,064	-5,858	2,252	-1,096	-1,543	-11,799	13,328	-2,095**
PARCH-M										
intercept	-0,005		0,008			0,007			-0,018	-0,016*
garch-m	4,948	OF	1,455	OF	OF	0,458	OF	OF	13,646	0,703
Subsample 1994-2009										
GARCH-M										
Intercept	0,014**	0,027*	0,007	0,007	0,001		0,013	0,018	0,008	0,009
garch-m	-1,099	-5,382	0,216	-0,163	1,194	OF	-1,115	-1,294	-1,339	0,414
EGARCH-M										
intercept	0,014**	0,134**	0,011	0,009	0,003	0,033	0,011	0,021	0,007	0,005
garch-m	-2,468	-42,78**	-1,800	-1,251	0,137	-12,585	-1,656	-2,521	-1,721	0,328
PARCH-M										
intercept	0,012**	0,028**	0,015	0,011	0,003		0,013	0,019	0,006*	0,007
garch-m	-1,287	-6,889	-3,484	-1,773	0,031	OF	-1,949	-2,089	-1,138	0,120

* Significance p<5% ** Significance p<1% ***Singificance p<0,1% OF=Overflow, no convergence of the model.

CA = Canada, DK = Denmark, FR = France, GM = Germany, IT = Italy, JP = Japan, NL = Netherlands, SE = Sweden, UK = United Kingdom, US = United States

5.2.3 Monthly data with macro variables; set one

Due to the previous empirical results of this paper; the asymmetry in the chocks and the negative small sample properties of the PARCH-M model, the macro variables are only added to the EGARCH-M model[2]. The results are summarized in table 6.5 on the following page, for diagnostic test results see appendix A3.5.

The models with macro variables added to the mean equation and to the conditional variance, appear to be robust and show no signs of problems with autocorrelation or remaining ARCH effects in the standardized residuals. Neither, can the null hypothesises of normally distributed residuals be rejected for a majority of the countries.

The macroeconomic variables are generally greater in the conditional variance than in the mean equation, suggesting that they affect the conditional variance more than the macroeconomic variables in the mean equation affects the expected returns. However, almost all of the macroeconomic variables, both in the mean equation and in the conditional variance, are clearly insignificant. The exception is the term spread that is significant in the mean equation for Italy, Japan and the Netherlands. Further, the CPI and term spread are significant for Denmark in the conditional variance. Also all of the GARCH-M terms are insignificant, unlike the intercepts that are significant in about half of the countries in both models.

Therefore, adding the first set of macroeconomic variables does not appear to change the results regarding the relationship between expected returns and volatility significantly.

[2] As discussed previously, the empirical results of the PARCH-M model indicate that the model do not converge in small samples despite different starting values. Especially, monthly data frequency and small samples proved to be difficult when using the PARCH-M model.

Table 6.5

EGARCH-M Estimations with macro variables, SET ONE

Coefficient	**CN**	**DK**	**FR**	**GM**	**IT**	**JP**	**NL**	**SE**	**UK**	**US**
SET ONE										
mean eq,										
intercept	0,01	0,03	0,01	0,01	0,00	0,02	0,01	0,02	0,01	0,01
p-value	0,03	0,03	0,35	0,35	0,82	0,07	0,04	0,05	0,06	0,01
garch-m	-1,86	-6,48	-1,47	-1,85	1,17	-7,07	-2,99	-2,88	-1,84	-0,94
p-value	0,45	0,15	0,61	0,48	0,59	0,09	0,28	0,23	0,48	0,69
CPI	-0,09	-0,03	1,79	1,81	0,62	-0,10	-0,41	-0,08	1,71	-0,76
p-value	0,68	0,98	0,19	0,26	0,75	0,93	0,52	0,91	0,26	0,24
Ind Prod,	0,01	0,01	-0,02	-0,08	0,00	-0,05	-0,03	0,03	-0,02	0,11
p-value	0,84	0,79	0,35	0,18	0,85	0,29	0,42	0,25	0,35	0,28
TS	0,00	0,03	-0,01	0,01	-0,10	0,05	-0,03	0,03	-0,02	0,03
p-value	0,80	0,55	0,77	0,50	0,03	0,00	0,04	0,36	0,77	0,47
variance eq,										
arch*	0,48	0,17	0,28	0,31	0,31	0,03	0,43	0,26	0,04	0,37
p-value	0,00	0,09	0,03	0,05	0,02	0,81	0,00	0,01	0,81	0,00
asymetri*	-0,14	-0,18	-0,27	-0,13	-0,09	-0,18	-0,20	-0,13	-0,20	-0,23
p-value	0,02	0,02	0,00	0,10	0,03	0,01	0,00	0,02	0,01	0,00
garch*	0,81	0,83	0,75	0,86	0,92	0,91	0,83	0,88	0,71	0,89
p-value	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
with macro variables in variance eq,										
mean eq,										
intercept	0,01	0,04	0,01	0,01	0,00	0,04	0,01	0,03	0,01	0,01
p-value	0,01	0,00	0,42	0,54	0,84	0,19	0,02	0,02	0,04	0,03
garch-m	-3,08	-11,75	-1,38	-1,17	0,99	-17,43	-3,61	-4,35	-3,18	-0,64
p-value	0,23	0,20	0,63	0,66	0,65	0,20	0,22	0,09	0,23	0,78
CPI	-0,05	1,32	1,84	1,91	0,72	-1,61	-0,12	0,08	-0,07	-0,70
p-value	0,86	0,26	0,17	0,30	0,71	0,41	0,86	0,09	0,56	0,28
Ind Prod,	0,02	0,02	-0,01	-0,07	0,00	0,03	-0,03	0,02	0,02	0,12
p-value	0,66	0,36	0,56	0,23	0,97	0,73	0,42	0,37	0,46	0,22
TS	0,00	0,04	-0,01	0,01	-0,10	0,05	0,10	0,03	0,00	0,03
p-value	0,98	0,33	0,88	0,72	0,05	0,09	0,07	0,15	0,98	0,50
variance eq,										
arch	0,45	0,19	0,26	0,26	0,33	-0,01	0,40	0,18	0,26	0,34
p-value	0,00	0,03	0,05	0,13	0,03	0,92	0,00	0,03	0,13	0,02
asymetri	-0,15	-0,13	-0,28	-0,12	-0,10	-0,20	-0,17	-0,10	-0,22	-0,23
p-value	0,01	0,02	0,00	0,13	0,35	0,07	0,01	0,03	0,13	0,01
garch	0,79	0,91	0,75	0,85	0,93	-0,33	0,89	0,94	0,65	0,88
p-value	0,00	0,00	0,00	0,00	0,00	0,16	0,00	0,00	0,00	0,00
CPI	6,05	45,13	-29,86	-35,33	-3,89	-43,25	40,21	4,69	2,98	-21,01
p-value	0,46	0,04	0,39	0,25	0,83	0,06	0,07	0,50	0,83	0,12
Ind, Prod,	3,25	1,59	0,65	-1,72	0,39	0,65	-1,10	0,50	0,29	2,27
p-value	0,13	0,01	0,44	0,37	0,49	0,62	0,30	0,40	0,49	0,73
TS	0,68	-0,47	0,14	-0,10	-0,58	0,70	-0,97	-0,45	-0,58	0,19
p-value	0,47	0,41	0,91	0,67	0,49	0,20	0,23	0,19	0,39	0,85

* = Normal distribution

CA = Canada, DK = Denmark, FR = France, GM = Germany, IT = Italy, JP = Japan, NL = Netherlands, SE = Sweden, UK = United Kingdom, US = United States

CPI = Consumer Price Index, Ind. Prod. = Industrial Production, TS = Term Spread.

5.2.4 Monthly data with macro variables; set two

The results using monthly data and the second set of macro variables are summarized in table 6.6 on the following page, for diagnostic tests see appendix A3.5.

Using the second set of macro variables in the mean equation, the coefficient of the three months t-bill rate is positive and significant for the U.S. and the coefficient of the unemployment rate is negative and significant for the Netherlands. The coefficient of the ten year bond yield is also positive and significant for Japan, the Netherlands and UK. None of the GARCH-M terms are significant and the intercepts of the mean equation is only significant once.

When the macroeconomic variables also are included in the conditional variance, the coefficient of the t-bill rate and the CPI becomes significant in the mean equation for Canada and U.S. respectively for Canada, Italy, Japan, Netherlands and the U.S. But even if the variables are significant not much could be said about the nature of the relationship because the sign of the coefficients are positive for some countries and negative for some countries.

In the conditional variance is the CPI coefficient significant for Denmark, Italy, Japan and the U.S, a relationship that is mainly negative. A negative relationship between the conditional variance and the t-bill rate coefficient is significant for Canada, Denmark, Japan and U.S. There is also a negative and significant relationship between the bond yield coefficient and conditional variance for Canada, Italy and the Netherlands. Also the M1 coefficient and the unemployment coefficient are significant for Italy respectively for Denmark and Japan. Like the model with set one's macroeconomic variables, the size of the coefficients of the macroeconomic variables in the conditional variance suggests that they effect the conditional variance more than the macroeconomic variables in the mean equation affect the expected stock returns. As in the first model, none of the GARCH-M terms are significant and the intercepts of the mean equation is only significant once.

The models with the second set of macroeconomic variables appear to be robust and the results indicate that the second set of macro variables are more relevant for explaining expected returns and the conditional variance than the first set of macroeconomic variables. Although, the results do not indicate that the macroeconomic variables affect the relationship between expected stock returns and volatility significantly.

Table 6.6
EGARCH-M Estimations with macro variables, SET TWO

coefficient		CN	DK	FR	GM	IT	JP	NL	SE	UK	US
mean eq,											
intercept		0,01	0,01	0,01	0,01	0,00	0,11	0,01	0,02	0,02	0,00
	p-value	0,03	0,34	0,25	0,54	0,99	0,22	0,09	0,06	0,13	0,84
garch-m		-3,64	-1,80	-1,81	-0,66	0,67	-43,93	-2,92	-2,73	-2,78	-0,06
	p-value	0,20	0,64	0,52	0,79	0,79	0,18	0,27	0,33	0,53	0,59
CPI		-0,06	0,77	1,76	1,90	1,03	0,38	-0,39	-0,99	-0,67	-0,37
	p-value	0,80	0,49	0,25	0,23	0,65	0,75	0,60	0,34	0,50	0,01
Ind Prod,		0,00	0,01	-0,01	-0,08	0,01	0,04	-0,02	0,02	-0,05	0,26
	p-value	0,97	0,83	0,60	0,22	0,70	0,39	0,65	0,49	0,26	0,60
Tbill3		0,01	0,08	-0,03	0,18	0,09	0,01	-0,13	-0,02	0,04	1,35
	p-value	0,85	0,33	0,66	0,16	0,08	0,53	0,05	0,64	0,40	0,00
Bond10		0,10	0,11	-0,01	0,04	-0,12	0,12	0,20	0,11	0,23	-0,37
	p-value	0,22	0,22	0,89	0,10	0,26	0,01	0,02	0,28	0,05	0,67
m1		0,40	0,74	-0,10	0,08	0,08	0,28	0,19	-0,08	-0,41	0,31
	p-value	0,43	0,13	0,79	0,92	0,77	0,56	0,50	0,83	0,29	0,61
Unemp		0,18	0,00	-0,27	-0,03	0,00	-0,10	-0,24	0,12	-0,16	0,07
	p-value	0,20	0,99	0,57	0,95	0,55	0,46	0,04	0,20	0,43	0,44
variance eq,											
arch*		0,46	0,23	0,33	0,31	0,31	-0,07	0,64	0,41	0,91	0,37
	p-value	0,00	0,11	0,02	0,07	0,07	0,24	0,00	0,01	0,00	0,01
asymetri*		-0,13	-0,10	-0,26	-0,12	-0,07	-0,07	-0,28	-0,13	0,13	-0,57
	p-value	0,11	0,17	0,01	0,11	0,09	0,21	0,00	0,13	0,47	0,00
garch*		0,82	0,88	0,79	0,88	0,93	-0,62	0,70	0,81	0,62	0,98
	p-value	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
with macro variables in variance eq,											
mean eq,											
intercept		0,12	0,00	0,00	0,01	-0,01	0,16	0,01	0,02	0,01	0,00
	p-value	0,07	0,76	0,61	0,57	0,27	0,14	0,10	0,03	0,14	0,87
garch		-42,03	0,75	-1,14	-0,11	3,90	-75,99	-3,21	-2,40	-5,18	-0,05
	p-value	0,23	0,88	0,69	0,96	0,02	0,13	0,24	0,27	0,34	0,72
CPI		1,45	-1,05	2,41	1,43	-0,97	-3,29	0,11	-1,01	-0,51	-0,40
	p-value	0,04	0,51	0,12	0,39	0,67	0,20	0,90	0,37	0,59	0,01
Industrial Prod,		-0,27	0,01	-0,01	-0,07	0,01	-0,02	0,00	-0,01	-0,02	0,09
	p-value	0,11	0,76	0,71	0,26	0,56	0,88	0,97	0,76	0,77	0,87
Tbill3M		-0,22	0,13	-0,02	0,16	0,11	-0,10	-0,14	-0,01	0,00	1,34
	p-value	0,01	0,16	0,74	0,23	0,07	0,05	0,04	0,61	0,98	0,00
Bond10		-0,48	0,09	0,02	0,03	-0,02	0,36	0,14	0,12	0,17	-0,56
	p-value	0,04	0,32	0,77	0,13	0,86	0,00	0,10	0,25	0,17	0,60
M1		1,29	0,27	0,01	-0,37	0,07	1,40	0,50	0,40	-0,40	0,88
	p-value	0,27	0,58	0,98	0,67	0,84	0,35	0,07	0,34	0,50	0,28
Unemp		0,30	-0,29	-0,22	-0,15		1,22	-0,11	0,17	-0,03	0,07
	p-value	0,39	0,11	0,66	0,72		0,04	0,26	0,08	0,91	0,51
variance eq,											
arch		0,14	0,20	0,18	0,30	-0,12	0,00	0,81	0,87	0,83	0,62
	p-value	0,08	0,34	0,24	0,15	0,00	0,95	0,00	0,00	0,04	0,00
asymetri		-0,04	0,08	-0,26	-0,08	-0,21	-0,04	-0,17	-0,19	-0,21	-0,52
	p-value	0,18	0,53	0,00	0,35	0,00	0,22	0,23	0,13	0,29	0,00
garch		-0,18	-0,24	0,83	0,73	0,92	-0,22	0,53	0,57	0,60	0,93
	p-value	0,02	0,12	0,00	0,00	0,00	0,05	0,00	0,00	0,00	0,00
CPI		8,97	101,71	-71,90	-64,08	-27,37	-29,62	53,83	20,73	48,05	-17,60
	p-value	0,08	0,01	0,16	0,15	0,03	0,03	0,09	0,59	0,45	0,01
Ind, Prod,		-1,42	-1,10	0,33	-1,55	0,11	-0,11	0,06	-0,40	4,61	-21,76
	p-value	0,21	0,20	0,76	0,49	0,91	0,87	0,97	0,71	0,18	0,08
Tbill3M		-1,61	-6,31	-0,11	-2,37	0,43	-0,60	-1,32	-0,18	-1,00	-6,56
	p-value	0,00	0,00	0,94	0,32	0,50	0,04	0,51	0,84	0,76	0,02
Bond10		-3,60	0,29	-1,14	-0,30	-2,41	1,28	-7,79	-1,12	-4,95	-0,54
	p-value	0,02	0,91	0,56	0,47	0,00	0,13	0,01	0,76	0,44	0,99
M1		4,56	34,98	-11,60	29,12	-13,69	6,13	-8,91	-7,50	0,51	-1,41
	p-value	0,60	0,05	0,28	0,07	0,00	0,52	0,37	0,53	0,98	0,96
Unemp		-0,61	14,24	-9,05	-4,39		7,15	0,66	-0,81	16,63	-0,16
	p-value	0,82	0,00	0,18	0,51		0,01	0,85	0,84	0,10	0,94

* = Normal distribution. CA = Canada, DK = Denmark, FR = France, GM = Germany, IT = Italy, JP = Japan, NL = Netherlands, SE = Sweden, UK = United Kingdom, US = United States Ind. Prod = Industrial Production, TBill3M = 3 Month Treasury Bill, Bond10=10 year Bond, Unemp.=unemployment.

5.3 Subsample period three – 2002-2008

To test if the results are different in a period of economic boom, daily and monthly data from the time period 2002-2008 were used. For the same reason as in section 6.2.3, only the EGARCH-M model will be used. The main findings are summarized in below table 6.7.

The results of subsample four confirm most of the previous results. Using daily data the ARCH and the GARCH terms are clearly significant and the GARCH term is generally greater than the then the ARCH term, see appendix A4.1 – A4.2. The asymmetry term is also clearly significant and negative. None of the GARCH-M terms are significant but the intercept of the mean equation is significant for Canada, Denmark, Germany, Italy and Sweden. The majority of the models seem to be robust except for France and UK where the standardized residuals indicate problems with autocorrelation.

Using monthly data, the intercepts of the mean equation are significant for Denmark, Germany, Italy, Sweden and UK. The GARCH-M term is significant for Germany, Sweden and UK. None of the models indicate any problem with autocorrelation or remaining ARCH effects.

When macro variables are added to the models especially the two interest rates are significant, see appendix A4.3 – A4.4. Also other macroeconomic variables are significant but as in the second sub sample period, the macroeconomic do not seems to affect the relationship between expected return and volatility in any important way.

Table 6.7
Significant Intercept and GARCH-Term no macroeconomic variables
GARCH-M, PARCH and EGARCH-M Estimations, 2002-2008

Coefficient	CN	DK	FR	GM	IT	JP	NL	SE	UK	US
EGARCH-M, Daily data										
intercept	0,001*	0,001***	0,00	0,001*	0,001*	0,00	0,00	0,001*	0,00	0,00
garch-m	-0,806	-3,571	0,348	-1,074	-2,009	0,014	-1,549	-2,707	1,438	-0,074
EGARCH-M, Monthly, data										
intercept	0,023	0,007*	0,013	0,008***	0,005*	0,086	0,009	0,020***	0,008**	0,027
garch-m	-15,116	-1,240	-7,186	-2,737***	-2,049	-37,728	-4,131	-5,103*	-7,106***	-6,210

6 Analysis and Conclusion

The purpose of this thesis is to examine the relationship between expected stock returns and volatility. Incited by the inconclusiveness of previous findings regarding the relationship, an extensive study is accomplished. Four different time intervals and time periods are examined, using three econometric models; the GARCH-M model, the PARCH-M model and the EGARCH-M model. Macroeconomic variables are also added to the models, both to the mean equation and to the conditional variance, to test for misspecifications of the models.

All three models have the coefficient c as an indicator of the relationship between volatility and expected stock return. In the full sample period the coefficient c shows no evidence of any significant long term relationship between expected return and volatility. The insignificant long term relationship occurs regardless of model. However, the results imply that there in some countries exists a significant short term relationship but that this relationship is both weak and unstable. Still, it appears as a significant relationship occurs more frequent among short term time periods during booms, i.e. economically advantageous periods. It also appears to be somewhat stronger and more stable when monthly data frequency is used instead of daily data frequency.

In contrast to the GARCH-M term, that seems to be more significant using monthly data, the intercept of the mean equation is in a greater extent significant using daily data. This suggests that on a daily basis, less of the expected returns are explained by volatility. On a monthly basis, this relation seems to be somewhat stronger and volatility is more important in explaining expected stock returns. The results also suggest that, although, the results generally indicates a negative relationship between expected stock returns and volatility, it appears as if the models that were used on monthly returns in a greater extent have a negative GARCH-M term then the models that were used on daily data.

In this study three different models were used and also expanded with macroeconomic variables to test for misspecifications of the mean equation and the conditional variance. However, there are still some signs of misspecification especially in the models that are based on daily data. Therefore we do not claim that our specifications are correct and that the models cannot be improved. It should also be kept in mind that the maximum likelihood function in EViews is dependent on which starting values that are used and that the quality of the estimates depends on how good they are. If the starting values are far from the real values the convergence achieved can be a local maximum and the quality of the estimate will be poor.

Because the results clearly suggest that there is asymmetry in the chocks and it proved difficult to estimate the PARCH-M model using smaller data sets, the EGARCH-M model was found to be the most appropriate model to model the relationship between expected stock returns and volatility. It was also found that none of the sets of macroeconomic variables increased the significance of the GARCH-M term. So, even if some of the individual macroeconomic variables are found to be significant in explaining expected stock returns, no further analysis of these relationships are preformed as explained in the introduction.

Overall, the results of this study indicate that there exists only a weak and insignificant long term relationship between expected stock returns and volatility, a finding that is consistent with the results of Baillie and DeGennaro (1990) and DeGennaro and Zhao (1997). This relation appears to be quite unstable, but generally the results indicate a negative relationship between volatility and stock returns, especially when the models are based on monthly data. The negative relationship between expected returns and volatility is in line with the findings of Glosten and Runkle (1993) but contradicts the assumptions of many modern asset pricing models that assume a positive relation between expected returns and volatility (Sharpe, 1964; Lintner, 1965; Merton, 1973).

An explanation for the negative relationship between expected stock returns and volatility is given by Li, Yang, Hsiao and Chang (2005) and is based on leverage (Black, 1976). They argue that such a negative relationship may be explained by the fact that a decrease in the stock value of a company cause an increase in the debt-to-equity ratio, which makes the stock riskier and increase its volatility. Another theory, also from Li, Yang, Hsiao and Chang (2005), is based on volatility feedback. It says that if volatility is priced then an increase of the volatility will cause the price of the stock to fall because the required return on equity increases. The latter, could explain why the models in this thesis that are based on monthly data in a greater extent have negative GARCH-M terms than the models based on daily data. On a daily basis the increase in volatility attracts investors, this cause an immediate increase in the stock price but in the long term the required return on equity increase and the prices falls, i.e. negative returns. Hence, this could also be the reason why volatility explains the monthly expected return in a greater extent than it explains expected daily returns.

To summarize, the main finding of this paper is that no significant long term relationship could be identified between volatility and expected return on the international market. However, on the short term a weak and unstable relationship could be found in some markets. Furthermore, the results suggest that there exists a positive but insignificant, daily, short term relationship and a negative also mostly insignificant, monthly, long term relationship between expected returns and volatility. This paper also found evidence that volatility explains the expected stock returns in a greater extent on a monthly basis than it does on a daily basis.

6.1 Further Research

During this research some further questions emerged that are interesting for future research. Focus should be on three different extensions. The first is to enlarge the data sample with more countries, as a possible basis for individual comparisons. For example, to compare large and small industrialized countries to see if the relationship between expected stock returns and volatility differs. The second extension suggests using other macroeconomic variables than those applied in this thesis, to see if these can further investigate possible misspecifications of the models. Finally, the last extension is the application of more advanced models, for example semiparametric models, to investigate the relationship between expected return and volatility.

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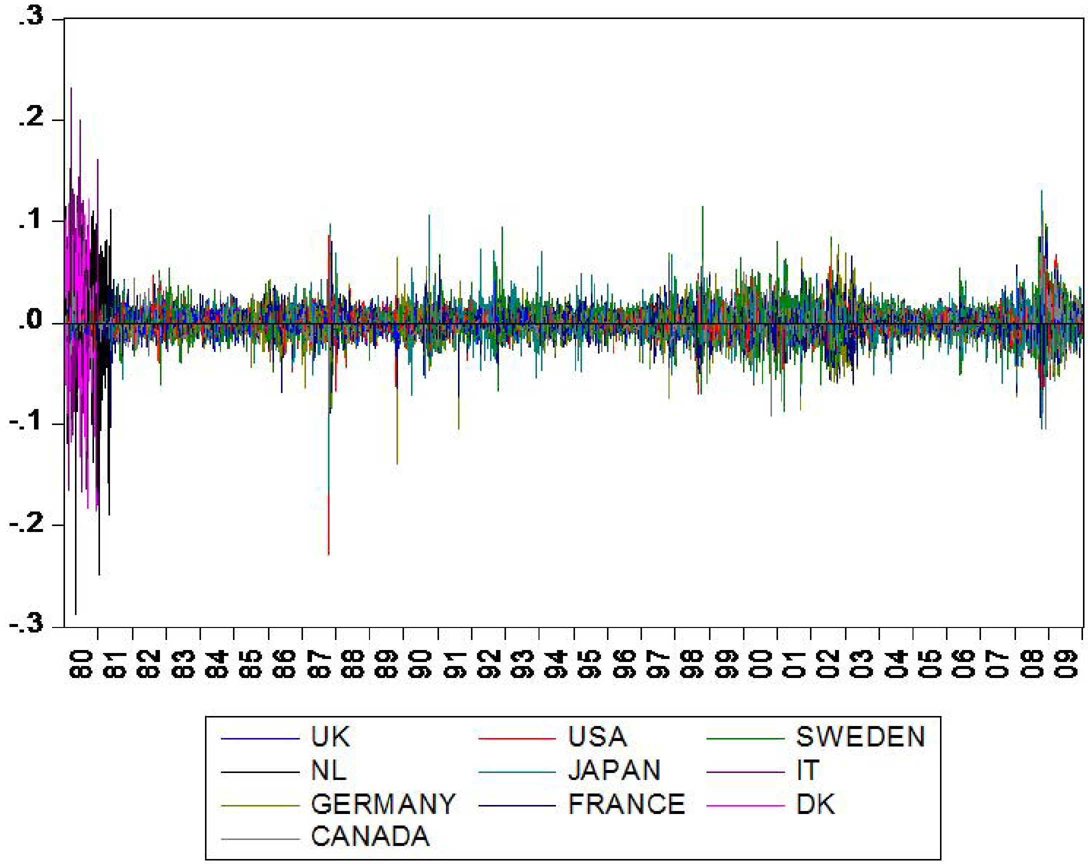
8 Appendix

A1 – Figure of log-returns



A2 – Results; 1980-2009

A2.1 – Diagnostic Tests - 1980-2009

Diagnostic tests, 1980-2009, Daily Data

Test	CN	DK	FR	GM	IT	JP	NL	SE	UK	US
GARCH-M										
Jarque-bera	3957,95	9498,19	3670,12	923320,97	4216,20	8146,83	2630,44	5855,66	4934,80	19422,59
p-value	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Correlogram	36+	0	0	0	0	1	0	0	17	2
ARCH LM test	36+	1	1	1	1	2	1	1	18	3
Q-statististic	36+	36+	36+	36+	36+	36+	0	36+	36+	23
Akaike	-6,76	-6,52	-6,26	-6,26	-6,06	-6,34	-6,37	-6,02	-6,56	-6,59
EGARCH-M										
Jarque-bera	3020,86	13932,59	5624,49	35116,76	3649,23	9058,00	1524,05	5165,77	2543,74	8790,78
p-value	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Correlogram	36+	5	0	0	3	1	0	0	36+	0
ARCH LM test	36+	6	1	1	4	2	1	1	36+	1
Q-statististic	36+	36+	36+	36+	36+	36+	0	36+	36+	22
Akaike	-6,76	-6,53	-6,27	-6,27	-6,07	-6,36	-6,37	-6,02	-6,56	-6,60
EGARCH-M										
Jarque-bera	3113,35	12034,63	4612,10	41692,50	4091,34	11303,64	1741,23	5323,70	3615,32	8052,16
p-value	0,00	0,00	0,00		0,00	0,00	0,00	0,00	0,00	0,00
Correlogram	36+	8	0		0	0	0	0	18	0
ARCH LM test	36+	9	1		1	1	1	1	19	1
Q-statististic	36+	36+	36+	36+	36+	36+		36+	36+	20
Akaike	-6,76	-6,53	-6,27	-6,27	-6,07	-6,35	-6,38	-6,02	-6,56	-6,60

*Squared Residuals

Diagnostic tets, 2002-2008, Monthly Data

Test	CN	DK	FR	GM	IT	JP	NL	SE	UK	US
GARCH-M										
Jarque-bera	228,88		133,85	190,50	11,92	21,95	239,90	32,79	1074,32	41,77
p-value	0,00		0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Correlogram	0		0	0	0	0	0	0	0	0
ARCH LM test	1		1	1	1	1	1	1	1	1
Q-statististic	0		1	0	36+	4	0	5	0	0
Akaike	-3,32		-2,85	-2,86	-2,56	-2,96	-3,04	-2,52	-3,35	-1,55
EGARCH-M										
Jarque-bera	165,59	10,63	44,48	127,53	7,90	7,69	133,20	35,00	1141,99	11,08
p-value	0,00	0,00	0,00	0,00	0,02	0,02	0,00	0,00	0,00	0,00
Correlogram	0	0	0	0	0	0	0	0	0	0
ARCH LM test	1	1	1	1	1	1	1	1	1	1
Q-statististic	0	0	0	0	36+	0	0	0	0	0
Akaike	-3,32	-2,96	-2,87	-2,80	-2,54	-2,98	-3,05	-2,52	-3,36	-1,60
EGARCH-M										
Jarque-bera	242,96		37,48	190,26	9,06	5,60	72,78	32,57	1349,83	7,55
p-value	0,00		0,00	0,00	0,01	0,06	0,00	0,00	0,00	0,02
Correlogram	0		0	0	0	0	0	0	0	1
ARCH LM test	1		1	1	1	1	1	1	1	1
Q-statististic	0		1	0	36+	0	0	0	0	0
Akaike	-3,32		-2,88	-2,85	-2,53	-2,97	-3,01	-2,52	-3,36	-1,59

A3 – Results; 1980-1993 and 1994-2009

A3.1 – GARCH-M, PARCH-M and EGARCH-M Results, 1980-1993 Daily Frequency

Daily data 1980-1993

GARCH-M, PARCH and EGARCH-M Estimations

Coefficient	CA	DK	FR	GM	IT	JP	NL	SE	UK	US
GARCH-M										
intercept	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	OF
p-value	0,36	0,06	0,00	0,07	0,42	0,05	0,00	0,00	0,01	
garch	2,78	-0,26	0,11	2,20	3,41	1,93	-1,48	1,39	-0,97	
p-value	0,32	0,93	0,97	0,33	0,06	0,24	0,55	0,49	0,80	
arch*	0,07	0,08	0,10	0,07	0,08	0,14	0,07	0,11	0,08	
	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	
EGARCH-M										
intercept	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
p-value	0,30	0,04	0,00	0,10	0,58	0,02	0,00	0,00	0,01	0,90
garch	2,68	-0,62	-1,80	2,30	3,55	-0,02	-1,51	0,73	-2,65	5,69
p-value	0,36	0,83	0,50	0,33	0,05	0,99	0,57	0,72	0,50	0,08
arch*	0,14	0,19	0,20	0,15	0,17	0,24	0,16	0,22	0,16	0,08
p-value	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
asymetri*	-0,01	0,00	-0,04	-0,02	-0,02	-0,09	-0,02	-0,02	-0,02	-0,03
p-value	0,13	0,76	0,00	0,02	0,07	0,00	0,00	0,08	0,11	0,00
garch*	0,99	0,97	0,96	0,99	0,98	0,97	0,98	0,97	0,96	0,99
p-value	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
PARCH-M										
intercept	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	OF
p-value	0,33	0,03	0,00	0,06	0,37	0,01	0,00	0,00	0,01	
garch	2,40	-0,91	-2,03	1,50	2,87	-0,69	-1,62	0,41	-1,94	
p-value	0,39	0,75	0,43	0,51	0,11	0,67	0,53	0,84	0,61	
arch*	0,07	0,10	0,11	0,08	0,09	0,14	0,08	0,11	0,08	
p-value	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	
asymetri*	0,02	0,03	0,18	0,12	0,09	0,35	0,06	0,07	0,07	
p-value	0,70	0,67	0,00	0,04	0,08	0,00	0,32	0,10	0,21	
garch*	0,91	0,91	0,86	0,92	0,91	0,88	0,91	0,87	0,88	
p-value	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	
power*	2,23	1,12	1,65	1,35	1,35	1,27	1,49	1,80	1,93	
p-value		0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	

* = Normal Distribution   OF = Overflow in EViews

CA = Canada, DK = Denmark, FR = France, GM = Germany, IT = Italy, JP = Japan, NL = Netherlands, SE = Sweden, UK = United Kingdom, US = United States

Diagnostic tests, 1980-1993, daily data

Test	CN	DK	FR	GM	IT	JP	NL	SE	UK	US
GARCH-M										
Jarque-bera	2989,96	9874,79	4442,65	111657,60	5123,50	10072,60	4003,29	9073,61	8442,39	
p-value	0,00		0,00		0,00	0,00	0,00	0,00		
Correlogram*	36+	1	0	0	0	0	2	0	10	
ARCH LM test	36+	2	1	1	1	1	3	1	11	
Q-statistic	36+	36+	36+	36+	36+	36+	0	36+	36+	
Akaike	-7,08	-6,77	-6,52	-6,58	-6,09	-6,70	-6,59	-6,35	-6,64	
EGARCH-M										
Jarque-bera	3092,07	12813,13	7127,28	69896,89	4506,65	9123,76	2457,40	8902,85	5226,77	33550,70
p-value	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Correlogram*	36+	4	0	0	0	0	10	0	36+	7
ARCH LM test	36+	5	1	1	1	1	11	1	36+	8
Q-statistic	36+	36+	36+	36+	36+	36+	0	36+	36+	12
Akaike	-7,08	-6,77	-6,51	-6,58	-6,09	-6,71	-6,59	-6,34	-6,63	-6,74
PARCH-M										
Jarque-bera	2775,00	12657,32	5445,24	85900,27	4932,66	8504,97	3036,88	9156,84	7160,74	
p-value	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	
Correlogram *	36+	7	0	0	0	1	7	0	5	
ARCH LM test	36+	8	1	1	1	2	8	1	6	
Q-statistic	36+	36+	36+	36+	36+	36+	0	36+	36+	
Akaike	-7,08	-6,77	-6,52	-6,58	-6,09	-6,71	-6,59	-6,35	-6,64	

*Squared Residuals

A3.2 – -M, PARCH-M and EGARCH-M Results, 1994-2009 Daily Frequency

Daily Data – 1994-2009
GARCH-M, PARCH and EGARCH-M Estimations

coefficient	CN	DK	FR	GM	IT	JP	NL	SE	UK	US
GARCH-M										
intercept	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
p-value	0,00	0,00	0,02	0,00	0,10	0,89	0,00	0,00	0,03	0,00
garch	0,84	-0,69	0,81	0,73	1,39	1,85	0,61	-1,08	1,72	0,97
p-value	0,60	0,69	0,61	0,59	0,34	0,29	0,65	0,42	0,32	0,53
arch*	0,07	0,09	0,07	0,09	0,08	0,08	0,09	0,07	0,08	0,07
	0,00	0,00		0,00	0,00	0,00	0,00	0,00	0,00	0,00
EGARCH-M										
intercept	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
p-value	0,00	0,00	0,24	0,03	0,23	0,23	0,01	0,00	0,54	0,02
garch	0,63	-1,23	0,91	0,58	0,88	2,34	-0,17	-1,46	2,10	1,39
p-value	0,70	0,47	0,55	0,66	0,54	0,18	0,90	0,27	0,22	0,35
arch*	0,12	0,16	0,12	0,15	0,16	0,15	0,15	0,13	0,11	0,11
p-value	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
asymetri*	-0,05	-0,05	-0,08	-0,09	-0,06	-0,07	-0,08	-0,06	-0,10	-0,11
p-value	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
garch*	0,99	0,99	0,99	0,98	0,99	0,98	0,99	0,99	0,99	0,99
p-value	0,00	0,00	0,00	0,00	0,00	0,00	0,00		0,00	0,00
PARCH-M										
intercept	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
p-value	0,00	0,00	0,23	0,03	0,16	0,57	0,02	0,00	0,47	0,01
garch	0,34	-1,34	0,66	0,35	0,30	1,12	-0,30	-1,35	1,52	0,66
p-value	0,83	0,43	0,65	0,78	0,83	0,51	0,82	0,30	0,34	0,64
arch*	0,07	0,08	0,06	0,08	0,09	0,07	0,07	0,07	0,06	0,05
p-value	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,76
asymetri*	0,39	0,30	0,64	0,55	0,29	0,45	0,45	0,45	0,95	1,00
p-value	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,84
garch*	0,94	0,92	0,93	0,92	0,91	0,92	0,92	0,93	0,94	0,94
p-value	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
power*	1,33	1,49	1,36	1,23	9,44	7,01	1,70	1,25	1,17	1,26
p-value	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00

* = Normal Distribution

OF = Overflow in EViews

CA = Canada, DK = Denmark, FR = France, GM = Germany, IT = Italy, JP = Japan, NL = Netherlands, SE = Sweden, UK = United Kingdom, US = United States

Diagnostic tets, 1994-2009, daily data

Test	CN	DK	FR	GM	IT	JP	NL	SE	UK	US
GARCH-M										
Jarque-bera	1191,92	497,97	175,02	314,64	497,97	420,89	194,85	188,51	161,46	934,45
p-value		0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Correlogram	0	0	18	4	0	0	12	0	0	0
ARCH LM test	1	1	19	5	1	1	13	1	1	1
Q-statististic	26	20	8	0	24	7	0	0	0	0
Akaike	-6,49	-6,32	-6,05	-5,98	-6,04	-6,03	-6,18	-5,74	-6,49	-6,46
EGARCH-M										
Jarque-bera	838,81	521,49	150,84	264,17	278,10	465,48	278,10	132,74	178,01	837,22
p-value	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Correlogram	0	0	0	27	7	36+	11	0	0	1
ARCH LM test	1	1	1	28	8	36+	12	1	1	2
Q-statististic	36+	26	36+	36+	8	7	0	0	36+	16
Akaike	-6,49	-6,33	-6,07	-6,00	-6,05	-6,05	-6,19	-5,76	-6,51	-6,48
PARCH-M										
Jarque-bera	884,42	525,82	147,87	244,71	228,92	431,75	248,52	128,35	190,05	774,69
p-value	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Correlogram	0	0	4	28	0	36+	5	0	0	1
ARCH LM test	1	1	5	29	1	36+	6	1	1	2
Q-statististic	36+	26	36+	36+	36+	8	0	0	36+	16
Akaike	-6,49	-6,33	-6,07	-6,00	-6,05	-6,05	-6,20	-5,76	-6,51	-6,49

*Squared Residuals

A3.3 – GARCH-M, PARCH-M & EGARCH-M Results, 1980-1993 Monthly Frequency

monthly data 1980-1993
GARCH-M, PARCH and EGARCH-M Estimations

coefficient	CA	DK	FR	GM	IT	JP	NL	SE	UK	USA
GARCH-M										
intercept	-0,03		0,01			0,01			0,00	-0,02
p-value	0,36		0,39			0,12			0,80	0,20
garch	14,71	OF	0,08	OF	OF	-0,15	OF	OF	4,49	1,12
p-value	0,28		0,99			0,94			0,51	0,20
arch*	0,01		0,10			0,15			0,07	0,26
p-value	0,65		0,55			0,11			0,64	0,08
EGARCH-M										
intercept	0,00	-0,58	0,11	0,03	-1,49	0,01	0,01	0,54	-0,02	-0,03
p-value	0,56	0,89	0,29	0,13	0,74	0,23	0,36	0,74	0,51	0,00
garch	4,59	202,49	-27,06	-5,86	289,25	-1,10	-1,54	-110,80	13,33	2,10
p-value	0,22	0,89	0,35	0,36	0,73	0,76	0,81	0,75	0,23	0,02
arch*	0,05	-0,02	0,01	0,29	0,00	0,36	0,21	0,04	-0,07	0,04
p-value	0,63	0,89	0,76	0,19	0,76	0,04	0,40	0,73	0,56	0,38
asymetri*	-0,10	0,01	-0,11	-0,17	0,01	-0,27	-0,10	-0,03	-0,20	-0,37
p-value	0,15	0,89	0,34	0,23	0,73	0,01	0,53	0,74	0,20	0,00
garch*	0,90	0,55	-0,49	-0,18	0,08	0,65	-0,36	0,07	0,50	0,89
p-value	0,00	0,00	0,03	0,67	0,88	0,00	0,59	0,78	0,11	0,00
PARCH-M										
intercept	-0,01		0,01			0,01			-0,02	-0,02
p-value	0,47		0,49			0,39			0,45	0,04
garch	4,95	OF	1,46	OF	OF	0,46	OF	OF	13,65	0,70
p-value	0,16		0,68			0,85			0,19	0,15
arch*	0,03		0,16			0,19			0,07	0,19
p-value	0,57		0,32			0,01			0,30	0,00
asymetri*	1,00		0,78			0,80			1,00	1,00
p-value	0,00		0,21			0,00			0,00	0,00
garch*	0,90		0,40			0,53			0,54	0,80
p-value	0,00		0,34			0,00			0,04	0,00
power*	0,22		0,63			0,45			0,50	0,62
p-value	0,61		0,57			0,31			0,41	0,08

* = Normal Distribution   OF = Overflow in EViews
CA = Canada, DK = Denmark, FR = France, GM = Germany, IT = Italy, JP = Japan, NL = Netherlands, SE = Sweden, UK = United Kingdom, US = United States

Diagnostic tests, 1980-1993, monthly data

Test	CN	DK	FR	GM	IT	JP	NL	SE	UK	US
GARCH-M										
Jarque-bera	153,94		122,60			24,96			716,68	50,91
p-value	0,00		0,00			0,00			0,00	0,00
Correlogram	0		0			0			0	0
ARCH LM test	1		1			1			1	1
Q-statistic	0		0			0			0	0
Akaike	-3,36		-2,76			-2,94			-3,16	-1,43
EGARCH-M										
Jarque-bera	452,99	106487,20	69,63	120,07	2399,93	5,90	289,57	28,45	1085,64	4,36
p-value	0,00	0,00	0,00	0,00	0,00	0,05	0,00	0,00	0,00	0,11
Correlogram	0	0	0	0	0	0	0	0	0	0
ARCH LM test	1	1	1	1	1	1	1	1	1	1
Q-statistic	0	0	0	0	0	0	0	0	0	0
Akaike	-3,36	-2,95	-2,78	-3,01	-2,30	-2,92	-3,21	-2,52	-3,18	-1,56
PARCH-M										
Jarque-bera	264,92		49,03			5,69			1065,25	7,27
p-value	0,00		0,00			0,06			0,00	0,03
Correlogram	0		0			0			0	0
ARCH LM test	1		1			1			1	1
Q-statistic	0		0			0			0	0
Akaike	-3,35		-2,76			-2,92			-3,18	-1,53

A3.4 – GARCH-M, PARCH-M and EGARCH-M Results, 1994-2009 Monthly data

monthly data, 1994-2009
GARCH-M, PARCH and EGARCH-M Estimations

coefficient	CN	DK	FR	GM	IT	JP	NL	SE	UK	US
GARCH-M										
intercept	0,01	0,03	0,01	0,01	0,00		0,01	0,02	0,01	0,01
p-value	0,01	0,04	0,42	0,51	0,89		0,11	0,10	0,13	0,10
garch	-1,10	-5,38	0,22	-0,16	1,19	OF	-1,11	-1,29	-1,34	0,41
p-value	0,63	0,25	0,94	0,95	0,65		0,67	0,60	0,67	0,39
arch*	0,37	0,14	0,20	0,18	0,19		0,31	0,16	0,23	0,29
	0,00	0,03	0,03	0,06	0,05		0,02	0,04	0,00	0,00
EGARCH-M										
intercept	0,01	0,13	0,01	0,01	0,00	0,03	0,01	0,02	0,01	0,00
p-value	0,01	0,00	0,13	0,40	0,73	0,11	0,15	0,07	0,14	0,42
garch	-2,47	-42,78	-1,80	-1,25	0,14	-12,58	-1,66	-2,52	-1,72	0,33
p-value	0,32	0,00	0,53	0,64	0,96	0,10	0,56	0,35	0,59	0,50
arch*	0,52	0,21	0,32	0,29	0,31	-0,05	0,45	0,25	0,40	0,42
p-value	0,00	0,00	0,01	0,03	0,03	0,55	0,00	0,01	0,00	0,00
asymetri*	-0,14	-0,04	-0,24	-0,12	-0,07	-0,20	-0,19	-0,09	-0,13	-0,15
p-value	0,03	0,03	0,01	0,09	0,10	0,03	0,01	0,11	0,05	0,03
garch*	0,81	-0,70	0,81	0,84	0,92	-0,62	0,84	0,92	0,86	0,95
p-value	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
PARCH-M										
intercept	0,01	0,03	0,02	0,01	0,00		0,01	0,02	0,01	0,01
p-value	0,00	0,02	0,63	0,29	0,71		0,07	0,06	0,05	0,31
garch	-1,29	-6,89	-3,48	-1,77	0,03	OF	-1,95	-2,09	-1,14	0,12
p-value	0,55	0,14	0,72	0,54	0,99		0,45	0,37	0,62	0,79
arch*	0,23	0,05	-0,03	0,12	0,16		0,23	0,05	0,18	0,16
p-value	0,37	0,61	0,93	0,21	0,08		0,01	0,67	0,02	0,14
asymetri*	0,24	0,37	-0,93	0,40	0,29		0,59	0,10	0,64	0,41
p-value	0,05	0,51	0,93	0,26	0,11		0,00	0,36	0,01	0,07
garch*	0,28	0,69	-0,57	0,71	0,81		0,64	0,65	0,71	0,75
p-value	0,29	0,00	0,27	0,00	0,00		0,00	0,00	0,00	0,00
power*	5,27	3,60	2,16	2,03	0,86		0,68	5,73	0,59	2,46
p-value	0,28	0,16	0,24	0,08	0,25		0,25	0,30	0,36	0,02

* = Normal Distribution
OF = Overflow in EViews
CA = Canada, DK = Denmark, FR = France, GM = Germany, IT = Italy, JP = Japan, NL = Netherlands, SE = Sweden, UK = United Kingdom, US = United States

Diagnostic tets, 1994-2009, monthly data

Test	CN	DK	FR	GM	IT	JP	NL	SE	UK	US
GARCH-M										
Jarque-bera	21,70	15,94	8,86	18,27	3,13		28,80	12,88	20,20	8,46
p-value	0,00	0,00	0,01	0,00	0,21		0,00	0,00	0,00	0,01
Correlogram	0	0	0	0	0		0	0	0	0
ARCH LM test	1	1	1	1	1		1	1	1	1
Q-statistic	0	0	0	0	0		0	0	0	0
Akaike	-3,27	-2,95	-2,92	-2,68	-2,75		-2,89	-2,54	-3,53	-1,64
EGARCH-M										
Jarque-bera	10,74	3,56	3,26	13,30	2,11	4,58	11,69	6,93	14,40	4,49
p-value	0,00	0,17	0,20	0,00	0,35	0,10	0,00	0,03	0,00	0,11
Correlogram	0	0	0	0	0	0	0	0	0	0
ARCH LM test	1	1	1	1	1	1	1	1	1	1
Q-statistic	0	0	0	0	0	0	0	0	0	0
Akaike	-3,28	-2,97	-2,96	-2,69	-2,76	-2,99	-2,91	-2,54	-3,55	-1,66
PARCH-M										
Jarque-bera	7,48	8,70	8,99	13,71	2,51		9,55	10,66	9,55	7,15
p-value	0,02	0,01	0,01	0,00	0,28		0,01	0,00	0,01	0,03
Correlogram	0	0	0	0	0		0	0	0	0
ARCH LM test	1	1	1	1	1		1	1	1	1
Q-statistic	0	0	0	0	0		0	0	0	0
Akaike	-3,29	-2,97	-2,80	-2,68	-2,74		-2,90	-2,54	-3,54	-1,65

A3.5 – Diagnostic Tests – Macro Variables 1994-2009

Diagnostic tests, 1994-2009, monthly data SET ONE

Test	**CN**	**DK**	**FR**	**GM**	**IT**	**JP**	**NL**	**SE**	**UK**	**US**
EGARCH-M with macro variables in mean eq.										
Jarque-bera	11,01	5,52	3,33	9,55	3,59	1,36	8,32	4,10		6,36
p-value	0,00	0,06	0,19	0,01	0,17	0,05	0,02	0,13		0,04
Correlogram	0	0	0	0	0	0	0	0		0
ARCH LM test	1	1	1	1	1	1	1	1		1
Q-statististic	0	0	0	0	0	0	0	0		0
Akaike	-3,37	-2,97	-2,96	-2,70	-2,67	-3,03	-3,06	-2,46		-3,68
EGARCH-M with macro variables in variance eq.										
Jarque-bera	6,88	0,96	3,11	9,87	2,88	1,15	6,56	2,84		5,88
p-value	0,03	0,62	0,21	0,01	0,24	0,56	0,04	0,24		0,05
Correlogram	0	0	0	0	0	0	0	0		0
ARCH LM test	1	1	1	1	1	1	1	1		1
Q-statististic	0	0	0	0	0	0	0	0		0
Akaike	-3,36	-2,99	-2,94	-2,67	-2,65	-2,97	-3,06	-2,45		-3,66

Diagnostic tests, 1994-2009, monthly data SET TWO

Test	**CN**	**DK**	**FR**	**GM**	**IT**	**JP**	**NL**	**SE**	**UK**	**US**
EGARCH-M with macro variables in mean eq.										
Jarque-bera	11,07	13,51	2,49	7,57	5,13	29,57	4,63	4,54		388,10
p-value	0,00	0,00	0,29	0,02	0,08	0,00	0,10	0,10		0,00
Correlogram	0	0	0	0	0	0	0	0		0
ARCH LM test	1	1	1	1	1	1	1	1		1
Q-statististic	0	0	0	0	0	0	0	0		0
Akaike	-3,24	-2,93	-2,91	-2,67	-2,72	-3,00	-2,91	-2,49		-0,53
EGARCH-M with macro variables in variance eq.										
Jarque-bera	2,13	3,45	2,20	6,56	2,98	0,57	4,84	4,75		47,61
p-value	0,26	0,18	0,33	0,04	0,23	0,75	0,09	0,09		0,00
Correlogram	0	0	0	0	0	0	0	0		0
ARCH LM test	1	1	1	1	1	1	1	1		1
Q-statististic	0	0	0	0	0	0	0	0		0
Akaike	-3,29	-2,96	-2,88	-2,69	-2,81	-3,06	-2,91	-2,42		-0,52

A4 – Results; 2002-2008

A4.1 – GARCH-M, PARCH-M and EGARCH-M Results, 2002-2008

GARCH-M, PARCH and EGARCH-M Estimations
Daily data, 2002-2008

Coefficient	CN	DK	FR	GM	IT	JP	NL	SE	UK	US
EGARCH-M										
intercept	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
p-value	0,01	0,00	0,52	0,05	0,03	0,30	0,11	0,01	0,72	0,39
garch	-0,81	-3,57	0,35	-1,07	-2,01	0,01	-1,55	-2,71	1,44	-0,07
p-value	0,75	0,11	0,85	0,53	0,35	1,00	0,36	0,15	0,49	0,97
arch*	0,12	0,16	0,10	0,11	0,09	0,17	0,12	0,10	0,09	0,08
p-value	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
asymetri*	-0,08	-0,10	-0,15	-0,13	-0,13	-0,09	-0,12	-0,11	-0,15	-0,12
p-value	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
garch*	0,99	0,98	0,98	0,99	0,99	0,98	0,99	0,99	0,98	0,99
p-value	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00

* = Normal Distribution

CA = Canada, DK = Denmark, FR = France, GM = Germany, IT = Italy, JP = Japan, NL = Netherlands, SE = Sweden, UK = United Kingdom, US = United States

Diagnostic tests, 2002-2008, daily data

Test	CN	DK	FR	GM	IT	JP	NL	SE	UK	US
EGARCH-M										
Jarque-bera	89,94	658,87	59,94	109,02	145,90	99,46	53,37	133,04	82,55	376,84
p-value	0	0	0	0	0	0	0	0	0	0
Correlogram*	0	0	0	0	0	0	0	0	0	0
ARCH LM test	1	1	1	1	1	1	1	1	1	1
Q-statististic	0	0	36+	0	1	0	0	0	36+	
Akaike	-6,56	-6,37	-6,14	-6,00	-6,45	-6,00	-6,15	-5,87	-6,54	-6,49

*=squared residuals

A4.2 – GARCH-M, PARCH-M and EGARCH-M Results, 2002-2008 Monthly Frequency

GARCH-M, PARCH and EGARCH-M Estimations
Monthly data, 2002-2008

Coefficient	CN	DK	FR	GM	IT	JP	NL	SE	UK	US
EGARCH-M										
intercept	0,02	0,01	0,01	0,01	0,00	0,09	0,01	0,02	0,01	0,03
p-value	0,11	0,03	0,19	0,00	0,01	0,13	0,43	0,00	0,01	0,18
garch	-15,12	-1,24	-7,19	-2,74	-2,05	-37,73	-4,13	-5,10	-7,11	-6,21
p-value	0,22	0,47	0,16	0,00	0,25	0,14	0,35	0,02	0,00	0,40
arch*	0,48	-0,39	-0,10	-0,32	-0,38	0,04	-0,11	-0,25	-0,50	0,37
p-value	0,07	0,00	0,50	0,00	0,00	0,66	0,57	0,00	0,00	0,09
asymetri*	-0,13	-0,33	-0,31	-0,30	-0,34	-0,20	-0,39	-0,24	-0,37	0,05
p-value	0,31	0,00	0,01	0,00	0,00	0,06	0,00	0,00	0,01	0,63
garch*	0,78	0,86	0,93	0,92	0,88	0,44	0,91	0,94	0,92	0,86
p-value	0,00	0,00	0,00	0,00	0,00	0,12	0,00	0,00	0,00	0,00

* = Normal Distribution
CA = Canada, DK = Denmark, FR = France, GM = Germany, IT = Italy, JP = Japan, NL = Netherlands, SE = Sweden, UK = United Kingdom, US = United States

Diagnostic tests, 2002-2008, monthly data

Test	CN	DK	FR	GM	IT	JP	NL	SE	UK	US
GARCH-M										
Jarque-bera	5,4	5,3	4,4	3,0	4,7	5,1	5,1	2,8	7,0	4,3
p-value	0,1	0,1	0,1	0,2	0,1	0,1	0,1	0,3	0,0	0,1
Correlogram*	0	0	0	0	0	0	0	0	0	0
ARCH LM test	1	1	1	1	1	1	1	1	1	1
Q-statististic	0	0	0	0	0	0	0	0	0	0
Akaike	-3,7	-3,1	-3,2	-2,8	-3,4	-3,0	-2,8	-2,8	-3,8	-2,8

* Squared Residual

A4.3 – EGARCH-M Results, 2002-2008; Macro Variables set one

EGARCH-M Estimations with macro variables
SET ONE

coefficient	CN	DK	FR	GM	IT	JP	NL	SN	UK	US
mean eq,										
intercept	0,02	0,01	0,01	0,01	0,00	0,01	0,00	0,02	0,01	0,00
p-value	0,08	0,10	0,26	0,27	0,98	0,40	0,58	0,00	0,31	0,00
garch	-13,61	-2,62	-7,39	-2,33	-2,37	-0,47	-3,12	-4,62	-8,21	0,09
p-value	0,19	0,23	0,14	0,25	0,34	0,92	0,38	0,01	0,17	0,00
CPI	-0,39	2,20	1,65	0,31	2,48	-1,65	2,18	2,65	1,01	-0,44
p-value	0,57	0,05	0,26	0,88	0,37	0,44	0,03	0,09	0,30	0,00
Ind Prod,	0,06	0,02	0,02	0,07	0,01	0,09	-0,06	-0,01	-0,01	0,75
p-value	0,40	0,42	0,50	0,33	0,56	0,11	0,46	0,71	0,87	0,00
TS	0,03	-0,10	0,05	0,01	-0,14	0,11	0,06	-0,04	-0,04	-1,39
p-value	0,58	0,24	0,47	0,72	0,06	0,00	0,65	0,66	0,61	0,00
variance eq,										
arch*	0,52	-0,36	-0,04	-0,32	-0,31	-0,20	-0,34	-0,36	-0,36	-0,38
p-value	0,10	0,00	0,81	0,00	0,00	0,00	0,05	0,00	0,14	0,00
asymetri*	-0,17	-0,26	-0,33	-0,33	-0,34	-0,22	-0,54	-0,22	-0,35	-0,42
p-value	0,24	0,00	0,01	0,00	0,00	0,05	0,00	0,01	0,00	0,00
garch*	0,81	0,91	0,92	0,91	0,88	1,01	0,85	0,95	0,92	0,98
p-value	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
with macro variables in variance eq,										
mean eq,										
intercept	0,03	0,12	0,01	0,01	0,03	0,02	0,02	0,04	0,03	0,00
p-value	0,06	0,01	0,30	0,16	0,00	0,02	0,01	0,01	0,00	0,31
garch	-26,41	-26,26	-5,93	-1,51	-11,39	-8,07	-6,96	-11,10	-18,45	0,04
p-value	0,11	0,52	0,21	0,57	0,09	0,18	0,12	0,07	0,07	0,65
CPI	2,02	3,38	0,96	-1,16	-4,16	-1,55	1,44	3,04	-1,77	-0,39
p-value	0,05	0,13	0,56	0,59	0,17	0,45	0,35	0,13	0,08	0,00
Ind Prod,	0,10	0,07	0,01	0,00	-0,04	0,04	-0,04	-0,09	0,03	0,58
p-value	0,34	0,31	0,75	0,99	0,02	0,53	0,64	0,12	0,61	0,22
TS	0,04	0,54	0,13	0,03	-0,19	0,10	-0,22	-0,04	0,30	-1,37
p-value	0,65	0,01	0,17	0,15	0,00	0,00	0,07	0,66	0,01	0,00
variance eq,										
arch	0,36	0,05	-0,15	-0,51	0,46	-0,17	0,00	-0,12	0,98	-0,36
p-value	0,06	0,53	0,41	0,08	0,04	0,00	1,00	0,04	0,01	0,00
asymetri	-0,10	-0,06	-0,37	-0,66	-0,54	-0,05	0,19	0,14	-0,18	-0,47
p-value	0,30	0,39	0,03	0,01	0,00	0,60	0,16	0,40	0,19	0,00
garch	0,57	-0,47	0,83	0,56	-0,46	1,00	1,02	0,96	0,50	0,99
p-value	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,02	0,00
CPI	56,21	20,23	-59,01	-98,95	-75,42	62,42	45,52	47,30	-31,70	-2,27
p-value	0,03	0,27	0,38	0,19	0,30	0,12	0,18	0,12	0,51	0,88
Ind, Prod,	1,57	0,72	-0,91	-6,08	-1,37	-2,84	-2,67	-2,54	5,56	29,32
p-value	0,65	0,10	0,48	0,07	0,00	0,55	0,25	0,16	0,09	0,31
TS	0,66	6,92	2,05	1,65	-1,97	0,13	-5,37	-1,73	2,53	-4,34
p-value	0,67	0,00	0,55	0,01	0,18	0,78	0,00	0,24	0,34	0,28

Diagnostic tests, 2002-2008, monthly data, SET ONE

Test	CN	DK	FR	GM	IT	JP	NL	SE	UK	US
EGARCH-M with macro variables in mean eq.										
Jarque-bera	3,78	1,93	4,33	3,36	3,98	3,76	3,80	1,10	6,34	177,06
p-value	0,15	0,38	0,11	0,19	0,14	0,15	0,15	0,58	0,04	0,00
Correlogram	0	0	0	0	0	0	0		0	36+
ARCH LM test	1	1	1	1	1	1	1		1	36+
Q-statististic	0	0	0	0	0	0	0		0	36+
Akaike	-3,61	-3,18	-3,20	-2,79	-3,37	-3,34	-2,79	-2,75	-3,67	-1,32
EGARCH-M with macro variables in variance eq.										
Jarque-bera	3,71	99,06	4,77	5,21	0,62	0,26	3,55	183,07	2,57	4498,95
p-value	0,16	0,00	0,09	0,07	0,73	0,88	0,17	0,00	0,28	0,00
Correlogram	0	0	0	0	1	0	0	36+	0	4
ARCH LM test	1	1	1	1	2	1	1	36+	1	5
Q-statististic	0	0	0	0	0	0	0	36+	0	36+
Akaike	-3,64	-3,07	-3,16	-2,79	-3,17	-3,29	-2,88	-2,80	-3,61	-1,33

A4.4 – EGARCH-M Results, 2002-2008; Macro Variables set two

EGARCH-M Estimations with macro variables, SET TWO

coefficient		CN	DK	FR	GM	IT	JP	NL	SE	UK	US
mean eq,											
intercept		0,02	-1,07	0,00	-0,21	-0,01	0,00	0,01	-0,29	0,02	0,00
	p-value	0,21	0,65	0,84	0,73	0,15	0,88	0,37	0,59	0,14	0,00
garch		-19,64	480,58	-1,72	57,80	-2,18	0,63	-1,80	78,48	-6,84	0,10
	p-value	0,20	0,64	0,62	0,72	0,31	0,91	0,23	0,62	0,36	0,02
CPI		-0,17	0,86	1,62	-0,28	4,88	-0,75	-0,66	2,35	-1,04	-0,44
	p-value	0,81	0,56	0,27	0,91	0,05	0,73	0,55	0,28	0,33	0,00
Ind Prod,		0,06	-0,01	0,04	0,03	0,00	0,09	0,08	-0,05	0,00	0,97
	p-value	0,39	0,70	0,24	0,83	0,86	0,10	0,01	0,20	0,98	0,23
Tbill3		-0,02	0,26	0,12	0,77	0,18	-0,09	0,16	0,39	0,11	1,41
	p-value	0,66	0,08	0,28	0,00	0,00	0,05	0,13	0,03	0,49	0,00
Bond10		-0,12	-0,16	0,22	0,05	-0,19	0,12	0,24	0,16	0,14	0,41
	p-value	0,39	0,22	0,07	0,33	0,07	0,01	0,01	0,36	0,36	0,00
m1		0,84	0,38	0,34	-1,47	0,93	2,61	0,44	0,65	-0,40	0,64
	p-value	0,28	0,62	0,28	0,32	0,00	0,06	0,06	0,17	0,31	0,56
Unemp		0,16	-0,66	0,70	-0,41		0,04	0,02	0,16	-0,25	-0,02
	p-value	0,35	0,00	0,09	0,57		0,85	0,79	0,23	0,29	0,82
variance eq,											
arch		0,55	0,02	-0,33	0,07	-0,44	-0,12	1,96	0,11	0,33	-0,33
	p-value	0,06	0,65	0,00	0,71	0,00	0,00	0,00	0,56	0,23	0,00
asymetri		-0,15	0,01	-0,29	0,02	-0,38	-0,17	-0,18	0,08	-0,11	-0,42
	p-value	0,21	0,65	0,01	0,79	0,00	0,07	0,49	0,53	0,44	0,00
garch		0,69	0,02	0,90	0,52	0,86	1,01	0,42	-0,01	0,93	0,98
	p-value	0,00	0,40	0,00	0,16	0,00	0,00	0,02	0,92	0,00	0,00
with macro variables in variance eq,											
mean eq,											
intercept		0,08	-1,06	0,00	0,02	0,01	0,05	0,00	-0,10	0,03	0,00
	p-value	0,12	0,62	0,38	0,18	0,25	0,01	0,66	0,09	0,00	0,55
garch		-84,78	475,85	-3,63	-4,31	-10,99	-31,23	-1,36	34,52	-24,87	0,10
	p-value	0,30	0,63	0,26	0,33	0,09	0,07	0,60	0,14	0,04	0,27
CPI		7,45	-2,11	-0,09	-1,20	2,15	-0,91	1,27	-10,28	-1,95	-0,36
	p-value	0,00	0,94	0,94	0,60	0,54	0,57	0,33	0,03	0,17	0,02
Industrial Prod,		0,02	0,13	0,07	-0,11	-0,04	0,26	0,02	0,15	-0,03	0,67
	p-value	0,92	0,85	0,00	0,24	0,09	0,00	0,69	0,30	0,61	0,11
Tbill3M		0,05	0,26	0,13	0,38	0,23	0,17	0,19	0,38	-0,24	1,38
	p-value	0,44	0,89	0,19	0,03	0,02	0,01	0,17	0,08	0,02	0,00
Bond10		-1,25	-0,85	0,41	0,02	-0,50	0,16	0,29	1,24	-0,07	-0,49
	p-value	0,00	0,76	0,00	0,62	0,00	0,00	0,01	0,01	0,57	0,37
M1		4,05	5,49	0,24	-0,22	1,07	-1,79	-0,01	0,22	0,47	0,23
	p-value	0,04	0,69	0,42	0,82	0,01	0,19	0,98	0,81	0,38	0,66
Unemp		-0,87	-1,15	0,15	0,62		0,86	0,02	0,37	-0,06	-0,01
	p-value	0,02	0,77	0,74	0,29		0,00	0,85	0,11	0,78	0,84
variance eq,											
arch		0,06	0,02	-0,89	-0,39	-0,41	0,65	1,04	0,27	1,15	-0,46
	p-value	0,33	0,64	0,00	0,19	0,10	0,03	0,03	0,11	0,01	0,12
asymetri		-0,12	0,01	-0,23	-0,24	-0,60	-0,15	-0,49	0,16	0,18	-0,65
	p-value	0,13	0,65	0,14	0,28	0,01	0,20	0,09	0,06	0,28	0,00
garch		0,08	0,02	0,68	0,24	-0,34	-0,10	0,51	-0,15	0,48	0,97
	p-value	0,17	0,63	0,00	0,28	0,04	0,40	0,01	0,36	0,02	0,00
CPI		67,12	3,28	-25,14	-147,67	-17,73	7,68	-16,02	98,47	104,12	-4,95
	p-value	0,00	0,90	0,30	0,03	0,90	0,89	0,80	0,02	0,09	0,78
Ind, Prod,		-0,58	-0,15	-0,79	-6,08	-1,74	2,47	2,39	-1,56	-1,67	15,38
	p-value	0,66	0,83	0,78	0,12	0,01	0,13	0,49	0,20	0,44	0,64
Tbill3M		0,71	0,00	-7,42	-8,42	1,75	2,69	-5,26	-1,11	-5,08	4,00
	p-value	0,38	1,00	0,01	0,21	0,28	0,00	0,38	0,69	0,11	0,39
Bond10		-10,50	0,67	4,60	0,44	-8,32	1,83	-12,36	-7,35	-6,70	35,76
	p-value	0,02	0,79	0,36	0,75	0,12	0,11	0,04	0,01	0,38	0,54
M1		29,72	-4,87	-17,90	95,94	12,71	-146,03	-18,12	4,93	15,94	84,88
	p-value	0,11	0,73	0,43	0,00	0,42	0,01	0,39	0,61	0,55	0,09
Unemp		-7,21	0,49	14,97	19,53		22,49	-6,21	-2,52	24,33	-0,79
	p-value	0,01	0,90	0,20	0,17		0,00	0,48	0,35	0,04	0,85

Diagnostic tests, 2002-2008, monthly data SET TWO

Test	**CN**	**DK**	**FR**	**GM**	**IT**	**JP**	**NL**	**SE**	**UK**	**US**
EGARCH-M with macro variables in mean eq.										
Jarque-bera	2,87	5,34	3,54	35,44	3,59	2,59	1,66	2,04	6,15	141,54
	0,24	0,07	0,17	0,00	0,17	0,27	0,43	0,36	0,05	0,00
Correlogram	12	0	0	29	0	0	0	0	0	36+
ARCH LM test	13	1	1	30	1	1	1	1	1	36+
Q-statististic	0	0	0	36+	0	0	0	10	0	36+
Akaike	-3,58	-2,93	-3,28	-2,53	-3,37	-3,30	-2,78	-2,51	-3,61	-1,23
EGARCH-M with macro variables in variance eq.										
Jarque-bera	326,40	4,49	3,15	2,26	3,61	0,27	2,75	2,35	1,65	14591,34
p-value	0,00	0,11	0,21	0,32	0,16	0,87	0,25	0,31	0,44	0,00
Correlogram	0	0	0	0	0	0	0	0	0	0
ARCH LM test	1	1	1	1	1	1	1	1	1	1
Q-statististic	0	0	0	36+	0	0	0	36+	0	3
Akaike	-3,88	-2,80	-3,21	-2,85	-3,15	-3,36	-2,74	-2,52	-3,76	-1,37