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Title:	**To return or not return – Trend spotting in the Swedish stock market**
Course:	Bachelor thesis (NEKK01)
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1 Introduction

The following section provides a quick introduction to the background of the subject of the efficient market hypothesis as well as the purpose of the following thesis. We will also give a brief summary about the methods used and the delimitations we have enforced. It ends with a disposition of the rest of the thesis.

1.1 Background

Within the field of finance people often dream of trying to find ways in order to exploit the market and thus create abnormal profits. Many economists argue that the stock market is efficient which makes it impossible to systematically earn money by trying to find trends in the historic stock prices. Others claim the opposite, that the stock market does not follow a random walk, it follows a trend which makes it possible to systematically beat the market and generate abnormal returns by trading stocks.

Critics of the well-established efficient market hypothesis (EMH) have developed statistical theories, as well as trading strategies in which they try to prove the shortcomings of the EMH, such as mean reversion, contrarian and momentum strategies. In the following thesis we will analyse whether stock prices indeed follow a random walk process, or if one could use the critics' strategies in order to beat the market.

1.2 Purpose

The purpose of the following thesis is to analyse whether the stocks at the Stockholm Stock Exchange exhibit a random walk which would then support the EMH. We will also have a look at whether one could use different trading strategies that are based on the market being inefficient in order to create abnormal returns.

1.3 Method

We will start by analysing whether the stock prices follow a random walk process or not. This will be done by applying extensive econometric analysis and tests, including Augmented Dickey-Fuller, KPSS and Phillips-Perron tests.

A mean-reverting process would mean that the market could be exploited and we will create portfolios consisting of the best/worst performing stocks in the market, create portfolios with these and compare their returns with a minimum-variance strategy and a passive buy-and-hold strategy using the OMX index.

1.4 Delimitations

Most of the previous research that we have found and looked at has focused on the US markets. We will thus limit ourselves to the Swedish stock market in order to supplement this research and investigate what kind of results we reach.

1.5 Disposition

The disposition of this thesis will be as follows,

Chapter	Content
2	**Theory and Methodology -** We will start by building a foundation upon which we will base our analysis, this is made up of the efficient market hypothesis (EMH) and quick introduction to what is meant with a random walk. Moving on to the mean reversion theory and the different methods we will use to test for this. The last section of this chapter deals with how we create our portfolios in order to check whether the trading strategies work or not, and how we will compare them.
3	**Previous Research –** This section starts by looking at the research that has previously been conducted within the area of the EMH, then moving on to look at research about whether the market follows a random walk or is mean reverting. Finally we will have a look at what has been reported about the trading strategies in the past.
4	**Data** – A brief rundown of what data we have used, how it has been collected, manipulated and analyzed.
5	**Empirical Analysis and Results** – Here we will tabulate the results from the mean reversion analysis using a small selection of the stocks and briefly explain how to interpret the values. For a full tabulation please have a look in the appendix. We will also present the findings from the different strategies.
6	**Discussion** – It is time to start discussing our results and the implications of the findings. The first subsections deals with the econometrical results, whilst the second deals with the strategies.
7	**Conclusion** – A brief conclusion that sum everything up. This section also includes some suggestions for future research.

2 Theory and Methodology

Before we start looking at the mean reversion theory, we believe that it would be useful to devote the following section to a few key theories at which the mean reversion theory directs criticisms and aims at rejecting. We will also have a look at the methodology used throughout the thesis and give general descriptions of these.

2.1 Efficient Market Hypothesis

The *Efficient Market Hypothesis* (EMH) has been one of the most fundamental theories in finance ever since it was developed by Eugene Fama in the 1960s. He defines an efficient market as one where:

> "…there are large numbers of rational, profit-maximizers actively competing, with each trying to predict future market values of individual securities, and where important current information is almost freely available to all participants." (*Fama, 1995*)

The EMH states that the price of a security fully reflects and incorporates all relevant information and that they are always traded at their fair value. Elton et al (*2007*) states that a necessary condition for investors to have an incentive to trade until this point is that there are no transaction costs. Since this is not true, they conclude that a better definition would be that "prices reflect information until the marginal cost of obtaining information and trading no longer exceed the marginal benefit". This makes it impossible for investors to either purchase undervalued stocks or sell stocks for inflated prices using the stock's historical values. As a consequence, it should be impossible to beat the market by market timing or stock selection. The only way to do so would be by adding additional risk (*Fama, 1995*).

According to Fama (*1970*), an efficient market can take on three forms:

Weak form efficiency: In its weak form, all information contained in historical prices is fully reflected in today's price, implying that they are following a random walk process. Should the weak form be true, it would make attempts of predictions on future prices based on technical analysis (i.e. historical prices) insufficient (*Elton et al, 2007, p.400*). However, there is a possibility of making abnormal returns by using fundamental analysis.

Semi-strong efficiency: The semi-strong form of efficiency holds that all publicly available information, such as financial statement and annual reports, is fully reflected in current stock prices. This, in turn means that the only way of getting abnormal returns is by accessing non-public information (such as inside information), making fundamental or technical analysis inadequate.

Strong-form efficiency: In its strong form, prices reflect all available information, making it impossible for investors with access to information relevant for prices to gain abnormal returns. Not even accessing non-public information gives the investor an advantage. Since history has shown that this is not the true, the strong form of efficiency is irrelevant to our study. Fama (*1970*) himself concludes that:

> "One would not expect such an extreme model to be an exact description of the world, and it is probably best viewed as a benchmark against which the importance of deviations from market efficiency can be judged."

However, the weak- and the semi-strong form of efficiency are by many still thought to be valid, making them more interesting to our further studies.

2.2 Random walk theory

When testing for the weak- and semi-strong form of market efficiency, the random walk theory serves as a beneficial tool. A price series that follow a random walk is said to be non-stationary (have a unit root) and its returns are serially uncorrelated (*Westerlund, 2005*). The theory rests on the assumption that successive returns are independent and that they are identically distributed over time (*Elton et al, 2007, p.403*). The meaning of "random" suggests that prices are a direct response only to new information. Depending on the state of the information, prices move unpredictably. A basic random walk formula can be written as:

$$\ln P_t = \ln P_{t-1} + \varepsilon_t$$

Where $\ln P_t$ and $\ln P_{t-1}$ is the logarithmic price at time t and t-1 and where ε_t is the residual with an expected value of zero and a constant variance.

This formula thus implies that today's price is a good prediction of tomorrows. From this follows that if the random walk hypothesis were to be proven correct, the weak form of the efficient market hypothesis must hold. (*Elton et al, 2007*). This would also mean that technical methods trying to describe or predict future stock prices are without value (*Fama, 1995*).

2.3 Mean reversion theory and methodology

The term *mean reversion* suggests that stock prices are stationary in their mean. That in the long run, they tend to revert themselves to their mean or average. Shocks to prices are said to be temporary which means that the returns are negatively autocorrelated at certain horizons.

This in turn implies that the returns are predictable based on lagged prices. It should be mentioned though, that if mean reversion exists in the stock exchange, it is thought to be slow moving and only detectable during long time series. (*Balvers et al, 2000*)

The aforementioned stresses the importance of three things: first, the necessity of long-, reliable time series. Second: the need of identifying a trend path or fundamental value path for the asset in question. And lastly, a big enough data sample. (*Balvers et al, 2000*)

The fact that scientists cannot come to an agreement on whether stock prices follow a random walk process or not, is important on two levels (see chapter 3). If they were to have a unit root, i.e. follow a random walk, then shocks to prices have a permanent effect and you therefore cannot predict future returns based on historical data. It can also lead to increased long-term volatility in the stock market.

If stock prices on the other hand are mean reverting, these shocks only have a temporary effect which gives the investor the possibility to predict future prices. This, in turn, means that trading strategies can be developed for generating abnormal returns. The most prominent being the momentum strategies (ordinary momentum and contrarian) which will tested more extensively later in this paper.

A logical first step would then be to test for random walk.

2.3.1 Unit Root

(Augmented) Dickey-Fuller

The following part of the study will test whether the prices of the stocks making up the OMXS30 during the second half of 2009 exhibit a mean-reverting process or if they follow a random walk. When testing for the random walk we will start by using the Dickey-Fuller method and Perron's (*1988*) testing procedure in order to establish whether a unit root exists or not.

The original Dickey-Fuller test builds upon the estimation of an AR(1) process,

$$\Delta y_t = \underbrace{(\rho - 1)}_{\rho^*} y_{t-1} + x_t^{'}\delta + \varepsilon_t \tag{1.1}$$

where x_t are optional exogenous regressors (constant and/or trend) (*EViews II, 2007, p.94*).

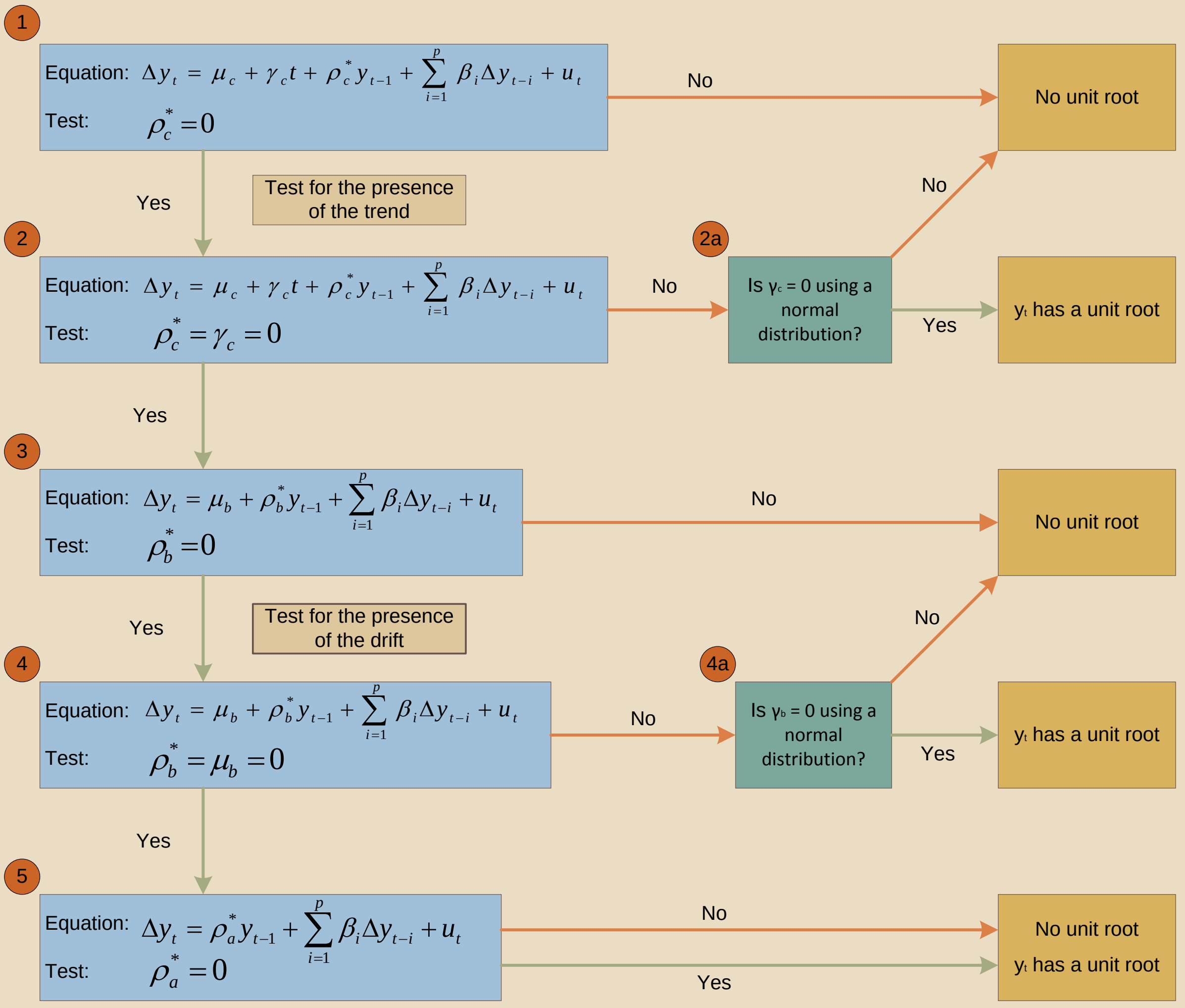
If ρ^* is equal to zero we have a unit root and the series is non-stationary, otherwise the series is stationary. What Dickey and Fuller (*1981*) showed was that in the case of a unit root the test statistic would not follow the t-distribution which had previously been used.

However, if the series is not an AR(1) process the unit root test above is not valid. If there occurs correlation at higher lag-orders ε_t cannot be considered as white noise; the augmented Dickey-Fuller (ADF) test constructs a parametric correction for correlations at higher orders than one by assuming an $AR(p)$ process instead (*EViews II, 2007, p.95*);

$$\Delta y_t = \rho^* y_{t-1} + x_t^{'}\delta + \sum_{i=1}^{p} \beta_i \Delta y_{t-i} + v_t \tag{1.2}$$

Perron (*1988*) outlines a testing procedure where one starts with a unit root equation which tests for different deterministic components and then sequentially reduces this one by removing the deterministic trend and drift.

Figure 1: Flowchart of the Perron (1988) testing procedure of the basic Dickey-Fuller, modification based on Enders (1995).



The first step (1) involves running the following regression,

$$\Delta y_t = \mu_c + \gamma_c t + \underbrace{(\rho_c - 1)}_{\rho_c^*} y_{t-1} + \sum_{i=1}^{p} \beta_i \Delta y_{t-i} + u_t \quad u_t \sim IID(0, \sigma^2) \tag{1.3}$$

We will go from a general model and work our way down towards a more specific model. Initially we will include both a constant and a trend, μ and γt, and start by checking whether the unit root coefficient is equal to zero.

Perron (*1988*) did not include any lags of the dependent variable, something which Enders (*1995*) recommends including to allow for higher orders of autoregressive terms. When running our models we will use the Schwarz Information Criterion (SIC) to decide how many lags we are to include. The SIC penalizes the addition of additional terms to the model , more than for example the Akaike Information Criterion (AIC) would do, and uses the following formula,

$$\mathrm{SIC} = -\frac{2\mathrm{l}}{\mathrm{T}} + \frac{\mathrm{k} \ln \mathrm{T}}{\mathrm{T}} \tag{1.4}$$

where l is the likelihood function, k is the number of estimated parameters and T is the number of observations. EViews will use this criterion to pick the optimal number of lags to include.

If the unit root is found to be insignificant we will perform a joint significance test of the unit root and trend coefficients. For this we use the following F statistic (*Verbeek, 2008, pp.27-29*),

$$\phi = \frac{(RSS_{restricted} - RSS_{unrestricted})/r}{RSS_{unrestricted}/(T-k)} \tag{1.5}$$

If the joint test is found to be significant we will use the normal distribution instead of the Fuller critical values, shown as step $(2a)$.

If we progress to step (3) we will remove the trend from our model since it has been found to be insignificant. We will once again check if the unit root is equal to zero, using the Dickey-Fuller critical values.

Step (4) is once again a joint significance test as in (2), however using the drift and unit root coefficient this time instead. If we reject our null hypothesis of $\rho_b^* = \mu_b = 0$ we will progress to $(4b)$ and use the normal distribution table when checking whether $\rho_b^* = 0$ or not.

The final step (5) is running our model without any stochastic terms. If ρ_a^* is found to be insignificant and we do not have any lags the model reduces down to,

$$\Delta y_t = u_t$$
$$y_t = y_{t-1} + u_t$$

Which is an autoregressive model of order one, AR(1) with $\rho = 1$, and thus is clearly non-stationary.

Phillips-Perron

Another unit root test is the Phillips-Perron (PP) test, which also builds on the Dickey-Fuller test. However, as opposed to the ADF which builds on including additional lags of the regressor, PP makes a non-parametric correction to the t-test statistic (*Phillips & Perron, 1988*);

$$\tilde{t}_\alpha = t_\alpha \sqrt{\frac{\gamma_0}{f_0}} - \frac{T(f_0 - \gamma_0)\sigma_{\hat{\alpha}}}{2\sqrt{f_0}s}$$

Where t_α is the t-ratio of α, s is the standard error of the test regression, γ_0 is a consistent estimate of the error variance. f_0 is an estimator of the residual spectrum at frequency zero (*EViews II, 2007, p.97*).

If the underlying serial correlation is not an AR(1) process, as assumed by Dickey-Fuller, the correction the PP test makes captures this discrepancy, as well as possible heteroskedasticity in the error terms (*Phillips & Perron, 1988*).

Kwiatkowski, Phillips, Schimdt and Shin (KPSS)

Previous standard unit root tests are often found to reject the null hypothesis of a unit root for many time series when analyzing economical data even though they should exist (type I error); Kwiatkowski, Phillips, Schmidt and Shin (*1992*) thus developed a new kind of test where they test,

$$H_0: \ Stationarity$$
$$H_1: Non - stationary\ (Unit\ root)$$

Classical hypothesis testing is often not very powerful against relevant alternatives, and many time series in economics are not informative enough about whether a unit root exists or not (*Kwiatkowski et al, 1992, p.160*).

The KPSS statistic is based on the residuals from the OLS regression (*EViews II, 2007, p.95*),

$$y_{.t} = x_t^{'}\delta + u_t$$
$$LM\ statistic = \sum_t \frac{S(t)^2}{T^2 f_0}$$

Where f_0 is the estimator of the residual spectrum at frequency zero and $S(t)$ is the cumulative residual function,

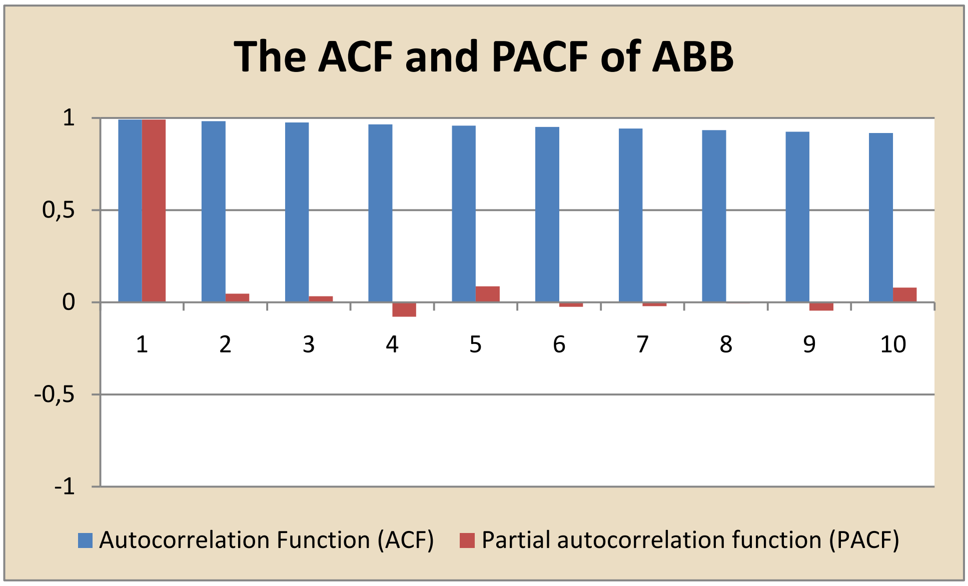
$$S(t) = \sum_{i=1}^{t} \hat{u}_r$$

Kwiatkowski et al (*1992, p.161*) derived the asymptotic distribution of the LM statistic shown above under general conditions of the stationary error.

2.3.2 Autoregressive and Moving Average Models

We will also have a look at what kind of models that fit the series of stock prices. When trying to figure out what kind of model we are to use we start by analyzing the autocorrelation function (ACF) and the partial autocorrelation function (PACF) at different lags. The figure below displays the first 10 lags of the ACF / PACF for ABB.

Figure 2: The autocorrelation and partial autocorrelation function of ABB.



Most of the stocks show a similar pattern, where the ACF is slowly decaying and the PACF has an initial spike at lag one and is subsequently zero.

Table 1: Properties of the ACF and PACF, extracted from Enders (1995).

Process	ACF	PACF
White noise	All $\rho_s = 0\ (s \neq 0)$	All $\phi_{ss} = 0$
AR(1): $a_1 > 0$	Direct exponential decay: $\rho_s = a_1^s$	$\phi_{11} = \rho_1; \phi_{ss} = 0\ for\ s \geq 2$
AR(p)	Decay towards zero, may oscillate.	Spikes through lag p. All $\phi_{ss} = 0\ for\ s > p.$
MA(1): $\beta > 0$	Positive spike at lag 1. $\rho_s = 0\ for\ s \geq 2$	Oscillating decay: $\phi_{ss} > 0$
ARMA(1,1)	Exponential decay beginning at lag 1.	Oscillating decay beginning at lag 1. $\phi_{ss} = \rho_1$
ARMA(p,q)	Decay beginning at lag q.	Decay after lag p.

The pattern of Figure 2 would thus indicate that we are dealing with an $AR(1)$ model,

$$AR(1): y_t = \rho y_{t-1} + x_t'\delta + u_t \tag{1.6}$$

However, since we have a very slow decay in the ACF this indicates that we might be dealing with a unit root (*Brocklebank and Dickey, 2003*). Although it is improbable that we are dealing with an ARMA(1,1) or AR(2) model we will include these in our tests in order to be thorough,

$$AR(2):\ y_t = \rho_1 y_{t-1} + \rho_2 y_{t-2} + x_t^{'}\delta + u_t$$
$$ARMA(1,1):\ y_t = \rho_1 p_{t-1} + u_t + \theta_1 u_{t-1}$$

Each model will be estimated and the coefficients will be checked for significance. We will compare the different models to each other using the Aikaike Information Criterion (AIC), Schwarz Information Criterion (SIC) and Theil's adjusted R^2.

2.3.3 Normal Distribution of the Residuals

Jarque-Bera

The first thing that will be analyzed is whether the residual series are normally distributed or not. If they are not, then our inference will be incorrect which will affect what kind of tests we are able to conduct and if we should use for example Newey-West heteroskedasticity consistent coefficient covariance (*Newey and West, 1987*).

An often used method for checking for normally distributed residuals is the Jarque-Bera (JB) test,

$$JB = \frac{N}{6}\left(S^2 + \frac{(K-3)^2}{4}\right)$$

This test has a look at the difference between the series skewness (S) and kurtosis (K) and compares these with those of a normal distribution, which has a S of 0 and K of 3. Under H_0 (a normal distribution) the JB statistic is equal to zero, and otherwise it's greater than 0. JB follows a χ^2 distribution with 2 degrees of freedom (*EViews I, 2007, p.308*).

2.3.4 Correlation of the residuals

We look at a few different methods used for checking for serial correlation in the residual series.

Durbin-Watson

An frequently used test is the Durbin-Watson (DW),

$$\mathrm{dw} = \frac{\Sigma_{t-2}^{T}(e_t - e_{t-1})^2}{\Sigma_{t-1}^{T} e_t^2}$$
$$\approx 2(1 - \hat{\rho})$$

where e_t is the OLS residual.

Durbin-Watson statistic is a test for first-order correlation, and thus tests the hypothesis of the residuals following an AR(1) process,

$$u_t = \rho u_{t-1} + \varepsilon_t \qquad (1.7)$$

There are a few limitations of the DW test explaining why we will not use it in our case (*EViews II, 2007, pp.64-65*);

- There will always be an inconclusive region upon which you can neither accept nor reject the null hypothesis.
- It is not valid if there are lagged dependent variables on the right-hand side of the regression.
- We only test the null of no correlation against H_1 of first-order serial correlation.

Since we will be dealing with autoregressive models we will be unable to use the d statistic since it is not applicable in this case (*Gujarati, 2006, p.437*). There are other tests which overcome these limitations which we will use instead when checking for autocorrelation.

Ljung-Box Test

The Ljung-Box is a statistical test that checks whether a group of coefficients from the autocorrelation function is different from zero or not, and is a portmanteau test (*Ljung and Box, 1978*).

The Q-statistic of the Ljung-Box test is equal to,

$$Q_{LB} = T(T+2)\sum_{j=1}^{k}\frac{A\hat{C}F_j^2}{T-J}$$

where T is the number of observations, k is the lag, and $A\hat{C}F_j$ is the estimated ACF at lag j.

$$H_0\!: \; Q_{LB} = 0 \; (White\ Noise)$$
$$H_1\!: \; Q_{LB} \neq 0 \; (Serial\ correlation)$$

We can see this from Table 1 above, that the ACF and PACF should be zero for the series to be constructed of white noise terms (*Enders, 1995*).

Breusch-Godfrey serial correlation LM test

The Breusch-Godfrey test checks for higher orders of serial correlation between the residual terms and can be used even though we include lagged regressors of the dependent variable.

The LM test has the null hypothesis that there is no serial correlation up to lag order p, where p is a pre-specified integer indicating how many lagged OLS residuals are to be used as extra explanatory variables.

2.3.5 Heteroskedasticity

One of the assumptions of the linear regression model is that the residuals are homoskedastic, if this does not hold the inference will be biased and the efficiency of the test is diminished (*Kennedy, 2009, pp.112-117*).

An often encountered form of heteroskedasticity in financial data is the autoregressive conditional heteroskedasticity (ARCH) which Engle (*1982*) introduced as “mean zero, serially uncorrelated processes with nonconstant variances conditional on the past, but constant unconditional variances”. These have since been generalized by Bollerslev (*1986*) into an GARCH(p,q) model,

$$\varepsilon_t|\psi_{t-1} \sim N(0, h_t)$$
$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j}$$

We will use an ARCH LM test in order to check whether the time series exhibits ARCH effects, that is, to check whether we can observe volatility clustering effects in the data.

One can also observe the correlogram of the squared residuals in order to get a overlook of whether the data is heteroskedastic. If the data has a non-constant variance then we will observe significant spikes at the ACF and PACF coefficients, and the probability values of the Q-stats will be less than our significance level.

2.3.6 Integrated and differenced series

When our first-order autoregressive process in (1.6) has a unit root it will be a random walk; non-stationary. We can rewrite an AR(1) process without any deterministic terms using the lag operator, L, as,

$$y_t = \rho_1 L y_t + u_t$$
$$(1 - \rho_1 L) y_t = u_t$$

The part of the equation with $(1 - \rho_1 L)$ is called the characteristic equation; only if the root of this is larger than 1 in absolute terms will the AR(1) process be stationary,

$$L = \frac{1}{\rho_1}$$
$$\Rightarrow |\rho_1| < 1$$

If the process were to be non-stationary we would say that it is an **integrated of order 1** series, denoted$I(1)$. In order to transform it into a stationary series, $I(0)$, we would take the first difference of the series,

$$y_t - y_{t-1} = \rho_1 y_{t-1} - y_{t-1} + u_t$$
$$\Delta y_t = (\rho_1 - 1) y_{t-1} + u_t$$

In the case of a unit root $\rho_1 = 1$ and the process would be reduced to,

$$\Delta y_t = u_t$$

Since u_t is a stationary, white noise, process it has the following properties,

$$E[u_t] = 0$$
$$var(u_t) = \sigma^2$$
$$cov(u_t, u_{t-k}) = 0$$

Since this holds for the residual term, the first-differenced time series will also be stationary.

2.4 Trading strategies

In the following section, we will have a look at two different trading strategies one can use; the contrarian strategy which builds on mean reversion, and a momentum strategy which builds on inertial continuation of the stock price movements.

The success of the contrarian strategy in creating abnormal returns would provide further indications of mean reversion existence. The inclusion of the momentum strategy is of interest due to its reverse assumption regarding trends; that stocks that have performed well in the past will continue to do so.

In order to get a sufficient amount of stocks when performing our analysis we will limit our time range to the period 2000-2009, which should suffice.

2.4.1 Portfolio constructions

Since there have been so many diversified findings previously within this field of finance, as we will discuss in the next section, we have decided to use a time horizon of 1, 3, 6 and 36 months when analyzing our different strategies. We adopt a strategy similar, though somewhat simplified, to the one used by Jegadeesh and Titman (*1993*), where we construct equally weighted portfolios consisting of the past winning and losing stocks.

They based their results using the highest and lowest deciles; however, due to a small number of stocks to choose from, we pick five stocks for each portfolio. Based on historic data stretching from January 2000 to the end of November 2009, we pick our stocks based on how they have performed during the past *J* months, where *J* is 1, 3, 6 and 36 months. The portfolios will then be held for *K* months where *K is* 1, 3, 6 and 36 months. In order to give more power to our tests, we construct new portfolios every month.

The two strategies will be compared to a simple buy-and-hold strategy which will be based on the OMXS30 index. We are aware of the anomalies that our choice of index presents. Since the OMXS30 is only updated two times each year, we cannot dismiss the possibility of distortion in form of a survivorship bias amongst the stocks. This might have effect when stocks that should be listed in the OMX30 are not and thereby not included in the portfolios (Haugen (2001). We also exclude relevant factors such as transaction costs, tax-effects and firm size when comparing portfolios.

When evaluating our portfolios, the Sharpe ratio is used as a measure of possible abnormal returns.

This formula can be written as

$$S_p = \frac{E[R_p] - r_f}{\sigma_p}$$

where $E[r_p]$ denotes the expected return of the portfolio, r_f is the risk-free rate and σ_p is the standard deviation of the portfolio (*Elton et al, 2007*)

The reason for using the Sharpe ratio is that it shows whether the portfolio return is due to good investing decisions or that the investor takes on additional risk. The Sharpe ratio is also referred to as an abnormal return to variability measure (*Elton et al, 2007*).

In our short portfolios, 1, 3 and 6-month t-bills will be used as the risk free rate. Since there does not exist Swedish 36-month bonds, we had to interpolate existing rates when calculating the profitability of our longer investment strategies. As the reader understands, this adds to the uncertainty of our findings. However, since the values are so low, it should not have that big of an impact.

When we have calculated the profitability of our strategies, the significance of our findings will be tested using a Student's t-test. The results will be tested against the null-hypothesis that the returns yielded by the portfolios are not significantly different from zero. Our t-values will be calculated using the following formula:

$$t = \frac{E[R_p] - \mu_0}{\sigma_p / \sqrt{N}}$$

where t denotes the t-value, $E[R_p]$ is the portfolios mean return, μ_0 is set to zero, σ_p is the standard deviation of the portfolio and N is the number of observations. Should any strategy earn greater returns than the market, the same test will be performed. For these tests, μ_0 would instead denote the average return of the index.

3 Previous research

In the following chapter, the reader is given a thorough review of the previous research performed in this field. Our main focus is being put on the influential articles that helps bring an understanding to the coming discussions.

The research in this field of financial economics goes back to the beginning of the previous century with the French mathematician Louis Bachelier. In his thesis, *Théorie de la Speculation,* he tried to model what he believed was the inherent randomness in stock prices, thereby laying the foundation of what was later to become the random walk hypothesis. (*Lo and MacKinlay, 1990*) This idea was further developed in the 1960's by Eugene Fama (and others) with the efficient market hypothesis (EMH). As mentioned earlier, an efficient market presupposes that one cannot use historical information in order to predict future stock prices thus implying that stock prices follow a random walk process.

Early studies of market efficiency showed autocorrelation of daily and weekly stock returns and found no evidence of serial correlation in stock prices. Since the estimated autocorrelations of short-horizon returns were close to zero, theses studies provided support for the random walk theory and the efficient market hypothesis. Fama (*1995*) distinguishes two ways of testing for random walk. One method is by using statistics where the dependence between price changes is tested using serial correlation coefficients and by analysing consecutive price changes. The other method is by developing trading strategies rules that aims at yielding higher return than the simple buy-and-hold strategy. In his paper, he states that to that date, no study using statistical tools has shown what he calls "*important dependence"* when analysing price changes in time series. Serial correlation tests by Cootner, Kendall and Moore and many others confirmed Famas results, also showing coefficients very close to zero (*Fama, 1995*).

Critics of the EMH and the random walk theory have pointed out that it is indeed possible earning abnormal return by means of technical- and fundamental analysis without taking on additional risk. This, as well as the anomalies that are said to exist in the stock market such as the January-effect effect (where returns are higher in January than other months) and the winner-loser effect (where previous stock performance appears to continue) would indicate market inefficiency (*Elton et al, 2007*)

Despite the criticism, no one could present sufficient proof of the market being inefficient for its advocates to reject it. As a consequence, these theories has remained very popular in this field for many years and it was not until the 1980's when researchers could present empirical evidence that stock prices followed a long-horizon trend. These findings would imply the possibility to predict future prices, thereby rejecting the random walk hypothesis and putting the EMH into question.

3.1 Random walk or mean reversion

Fama & French (*1988*) and Poterba & Summers (*1988*) were the first to put forward evidence of mean reversion occurrence in the U.S. stock prices over long time horizons. Their findings showed significant serial correlation in long-term stock returns, which would indicate that there exists a stationary component in stock prices.

By means of variance-ratio tests, Poterba & Summers found that stock returns were characterized by a positive autocorrelation over intervals under a year, and by negative autocorrelation over longer intervals (*Kim, Nelson and Startz, 1991*). Lo and MacKinlay (*1990*) used the same test method and came to the conclusion that the returns did not show a stochastic behaviour in accordance with the random walk theory, which has been used as evidence of mean reversion in stock prices. While previous research was able to detect anomalies in long horizon returns, Lo and MacKinlay could reject the random walk hypothesis using weekly returns.

Fama and French's findings were based on auto regressions on multilayer returns and showed that 25 to 40 percent of the variations in stock returns are predictable from past returns depending on whether it is small or large firms (*Fama and French, 1988*).

According to Fama, this does not necessarily mean that one should reject the EHM and random walk hypothesis. Together with French, he believes that:

> "...the predictability of long-horizon returns can also result from time-varying equilibrium expected returns generated by rational pricing in an efficient market" (*Fama and French, 1988, p.53*).

Meanwhile, several other researchers such as Kim, Nelson and Startz (*1991*), came to the opposite conclusion using different data or time frames, arguing that the Fama and French's findings were a pre-war phenomenon. Using post-war data, they argue that above average returns tends to be followed by yet another above average returns, calling it "*mean aversion*" (i.e. momentum). Their criticism aims at the use of Monte-Carlo simulations that presupposes that stocks are normally distributed when they are not. Also, the variance found in their test was not big enough to reject the random walk hypothesis. They also hold that the results very much depends on what market index- and type of return measure used. (*Frennberg and Hansson, 1993*)

Furthermore, Richardson and Stock (*1989*) even argued that the Fama and French´s findings might be reversed if correcting for small-sample bias problems (*Balvers, Wu and Gilliland, 2000*). Fama and French are also said to:

> "...avoid specifying a trend path by first-differencing the price series".

This leads to a loss of information which can be beneficial in finding a mean reverting price component. (*Balvers, Wu and Gilliland, 2000*). Kennedy (*2009*) on the other hand recommends doing the opposite; difference the data even due to the loss of efficiency.

More recent studies by Balvers et al. (*2000*) present strong evidence in favour of mean reversion in relative stock index prices, using data that stretches from 1969 to 1996. With cross-sectional power gained from national stock index data, they find a significantly positive speed of reversion with a half-life of three- to three and a half years.

Frennberg and Hansson (*1993*) are some of the few to test the random walk hypothesis in the Swedish stock market 1919 – 1990. They found strong evidence of positive auto correlated returns for short horizons and indications of negative autocorrelation over longer horizons (over two years or more), leading them to reject the random walk hypothesis.

Previous research has shown statistical evidence of mean reversion and stock price predictability, raising the question of what factors are behind this behaviour. One explanation is put forward by Shiller (*1984*). He states that predictability of stock prices is a result of market irrationality.

> "Fashions, fads or noise trading based on incorrect probability assessments can cause prices to deviate from their intrinsic values."

This, he holds, will eventually be corrected, leading to mean reversion and a possibility of predicting future prices. Another explanation is given by Fama and French (*1998*). Changes in investor preferences and changes in investment opportunities cause the equilibrium of expected returns to change over time.

As the reader might have noted, the previous research is this field is very much split. Depending on what test methods to use, what markets to analyze and what time span to test, the results vary. Advocates of the mean reversion theory use their results as a way of rejecting the efficient market hypothesis. Others, such as Kim et al (*1991*) question the statistical significance in these tests (*Frennberg and Hansson, 1993*).

Campbell, Lo and MacKinlay (*1997*) summarize the time frame problem with the following quote:

> "Overall, there is little evidence for mean reversion in long-horizon returns, though this may be more of a symptom of small sample sizes rather than conclusive evidence against mean reversion – we simply cannot tell."

3.2 Trading strategies

While much of the previous research aimed at presenting statistical evidence in order to test the EMH and RWH, others tried to develop strategies for trading in order to yield abnormal returns. Two of the most prominent strategies are the momentum- and contrarian strategy. Both of these are based on cross-sectional stock returns and presuppose that stock prices indeed follow a trend, implying the possibility of using technical analysis as a mean of beating the market (*Shen et al, 2005*).

3.2.1 Momentum strategy

The idea of the momentum strategy is quite simple. When an asset has performed relatively well in the past, investors believe that it is likely that they will continue to do so in the future (*Shen et al, 2005*). Investors will therefore take a long position in assets that historically have performed relatively well. This strategy can be combined with taking a short position in assets that have performed poorly, thereby creating a so called zero-investment portfolio (winner-loser). One of the more prominent articles on momentum is the one published by Jegadeesh and Titman (*1993*). Using monthly U.S data stretching from 1965-1989, they formed overlapping winner and loser portfolios consisting of the best (worst) performing stocks of the previous period. They found that over a time-horizon of three to twelve months, past winners on average continued to outperform past losers, which would indicate a momentum in stock prices (*Chan et al, 2000*).

A similar study was performed by Rouwenhorst (*1998*) in twelve European markets (including Sweden) 1980-1995. By constructing an internationally diversified portfolio buying medium-term winners and selling medium-term losers,   his zero-investment portfolios earns approximately 1 percent per month and continues to do so over the following year. After that, the momentum-effect appears to disappear.

3.2.2 Contrarian strategy

Advocates of the contrarian strategy take a slightly different approach to trends in stock prices compared to the momentum strategy. They believe that the market agents tend to overreact to unexpected and dramatic news. The contrarian strategy is based on the assumption of negative serial correlation of prices, i.e. price reversals. When implementing the strategy, the investor purchases an asset that has performed poorly in the past and sells short past winners. One of the most influential articles in this field is presented by De Bondt and Thaler (*1985*). While studying monthly data in the U.S market, they found that the stocks that performed poorly in the previous 3 to 5 years outperformed past winning stocks in the following 3 to 5 years, implying that the American stock market was inefficient.

In line with the previous research in the field of behavioural finance by the likes of Kahneman and Tversky (*1979*), they suggest that poor decision-making by investors leads them to overreact to new information, driving prices further up- or down depending on the type of news.

Fama and French give another explanation to why value strategies yields higher returns, the fact that they are fundamentally riskier and that the higher returns are merely compensation for this additional risk. Another explanation put forward is the size-effect (*Jegadeesh and Titman, 1993*). Critics of the findings of De Bondt and Thaler (see Ball and Kothari (*1989*)) use this argument as a way of dismissing the overreaction hypothesis (*Lakonishok et al, 1994*). Haugen (*1994*) takes a somewhat neutral position claiming that the stock market is overreacting, but slowly.

Jegadeesh (*1990*) and Lehmann (*1990*) came to similar conclusions using an even shorter time span (one week to one month). Jegadeesh's findings showed that the previous month's winners showed a significant negative return the following month. Interestingly, Lehmann found that even after taking transaction costs into consideration, the contrarian strategy yields significant profits. This view is not shared by Conrad et al (*1997*). They argue that these short-term profits come from the *"bid-ask bounce"* in transaction prices. After correcting for these, the profits disappear.

At a longer horizon, Conrad and Kaul (*1998*) investigated both of these strategies using eight different investment horizons. Their conclusion was that the two strategies did not contradict one another. In fact, both could exist but on different horizons. The momentum strategy was profitable on a 3 to 12 month period whilst the contrarian yielded abnormal returns on longer horizons, but only during 1926-1947. They also argue that cross-sectional variation has strong impact on the profitability of both strategies.

4 Data

The following section deals with the selection of the data, how it has been collected and transformed.

4.1 Data Selection

The data we have been working with consists of the 30 stocks that made up the OMXS30 during the second half of 2009.

4.2 Data Collection

We have used the database used by Thomson DataStream in order to retrieve the historic stock prices. Were possible the sample of the stock prices stretches between 30th of November 1989 until the 30th of November 2009. However, in certain cases the firms have not existed for the entire period and thus the sample starts when the stock was introduced at Stockholmsbörsen. All stock prices were based on the daily closing price.

4.3 Data Manipulation

Due to the vast amount of data and limitation of the statistical program used we decided to use the weekly closing pricing instead of the daily ones. We also transformed the prices into natural logarithms in order to make the calculations easier, especially when dealing with returns. This monotonic transformation does not affect the econometrical analysis.

4.4 Data Analysis

The data has been analysed using EViews for the mean reversion econometrical tests. Due to the sheer volume of repetitive tasks we have written programs that conduct all of the different tests and then save the results for us. For the analysis of the strategies we have used Microsoft Excel and created dynamic data sheets which search through our database with stock prices and then automatically updates depending on our entered parameters.

5 Empirical Analysis and Results

The following section contains the results from the empirical analysis of the stock prices. The tables only contain the first five stocks in each case in order to help understand how to read the different columns. For a full list of the findings, please refer to the appendix.

5.1 Unit Root

5.1.1 Augmented Dickey-Fuller

The table below shows a brief summary of the results from the ADF test. The results were found using a unit root test in EViews, and the F-tests in step 2 and 4 were manually programmed since there was no such test in the version of the program we were using.

	Observations	Step #1	Step #2	Step #3	Step #4	Step #5
ABB	545	0,805	1,662	0,543	1,100	0,573
Alfa Laval	394	0,426	2,713	0,828	0,293	0,923
Assa Abloy	786	0,243	7,610	-	-	-
Astra Zeneca	556	0,295	3,379	0,209	2,429	0,633
Atlas Copco	1044	0,096	4,979	0,831	0,285	0,961
Critical Value		0,05	6.30	0,05	4.61	0,05

See table 1 in appendix.

For the critical values at step 2 and 4 we have used an empirical distribution by Dickey and Fuller (*1981, p.1063*) with a sample size of 500.

5.1.2 Phillips-Perron

When using the Phillips-Perron test unit roots are found in all cases but one (Assa Abloy with only a constant) when using a 5% critical level. Some of the values are borderline to the critical level, and we will discuss this further in section 5.1.4.

	Trend & Constant		Constant		None	
	t-stat	p-value	t-stat	p-value	t-stat	p-value
ABB	-1,450	0,845	-1,368	0,599	-0,298	0,578
Alfa Laval	-2,101	0,543	-0,719	0,839	1,198	0,941
Assa Abloy	-2,610	0,276	-3,903	0,002	1,654	0,977
Astra Zeneca	-2,685	0,243	-2,353	0,156	-0,221	0,606
Atlas Copco	-2,947	0,148	-0,669	0,852	1,579	0,972

See table 2 in appendix.

5.1.3 KPSS Test

The KPSS test has the following asymptotically critical values when we include deterministic components,

	Constant	Trend and Constant
	Critical value	Critical value
1%	0,7390	0,2160
5%	0,4630	0,1460
10%	0,3470	0,1190

The KPSS test shows that two of the stocks are stationary when a constant is included (Boliden and Telia), and two other stocks when a trend is included as well (Astra Zeneca and Nokia).

	Constant		Trend & Constant	
	Bandwidth	Test statistic	Bandwidth	Test statistic
ABB	18	0,614	18	0,575
Alfa Laval	16	2,134	16	0,274
Assa Abloy	22	1,868	22	0,656
Astra Zeneca	18	0,709	18	0,116
Atlas Copco	25	3,751	25	0,199
Critical value		0,4630		0,1460

See table 3 in appendix.

5.2 ARMA models

5.2.1 The ACF and PACF

Below are the graphical representations of the coefficients of the autocorrelation function and partial autocorrelation function for the first ten lags. The ACF bars have a vertical axis scale of [0.7,1.0] and the PACF uses the scale [-0.2, 1.0].

As can be seen, all of the AFC graphs show a slow decrease in the coefficients as the lags increase, and a single spike at the PACF graphs. This supports that the prices are following an AR(1) model, while the slow decay indicates that we might be dealing with non-stationary data (*Brocklebank and Dickey, 2003*).

	ABB	Alfa Laval	Assa Abloy	Astra Zeneca	Atlas Copco	Atlas Copco B	Boliden	Electrolux
AFC								
PACF								

See table 4 in appendix.

5.2.2 Model comparisons

Below are the results from the first two models, AR(1) and ARMA(1,1). The columns show the value of the Akaike and Schwarz information criterion (AIC / SIC), the value of the characteristics root of the AR term, and the probability value of the MA term of the ARMA(1,1) model.

Model:	$y_t = \delta + \rho y_{t-1} + \varepsilon_t$			$y_t = \delta + \rho y_{t-1} + \varepsilon_t + \theta\varepsilon_{t-1}$			
	AIC	SIC	AR Root	$P_{MA(1)}$	AIC	SIC	AR Root
ABB	-2,057	-2,041	0,992	0,064	-2,059	-2,035	0,993
Alfa Laval	-2,872	-2,852	0,996	0,032	-2,876	-2,845	0,997
Assa Abloy	-3,135	-3,123	0,992	0,002	-3,143	-3,126	0,993
Astra Zeneca	-3,545	-3,530	0,977	0,004	-3,557	-3,534	0,983
Atlas Copco	-3,193	-3,183	0,999	0,008	-3,197	-3,183	0,999

See table 5 in appendix.

And below is the result from the AR(2) model, showing the probability value of the AR(2) coefficient, AIC, SIC, and the two characteristics roots of the AR terms.

Model: $y_t = \delta + \rho_1 y_{t-1} + \rho_2 y_{t-2}$

	$P_{AR(2)}$	AIC	SIC	AR Root 1	AR Root 2
ABB	0,098	-2,056	-2,033	0,993	-0,072
Alfa Laval	0,117	-2,872	-2,841	0,997	-0,080
Assa Abloy	0,006	-3,143	-3,125	0,992	-0,099
Astra Zeneca	0,003	-3,562	-3,538	0,982	-0,129
Atlas Copco	0,011	-3,196	-3,182	0,999	-0,079

See table 5 in appendix.

When using Akaike as our information criteria the ARMA(1,1) has the lowest value 15 times, whilst the AR(1) is preferred 12 times and AR(2) only three times. For the Schwarz criterion ARMA(1,1) is only preferred 5 times, and the AR(1) 24 times.

We also notice that in the case with the ARMA(1,1) model the MA(1) coefficient is insignificant in a majority of the regressions. The same thing is observed with the AR(2) coefficient when we run the AR(2) model.

The last thing which can be observed is that all of the autoregressive characteristics roots (column labelled "AR Root") are very close to unity, and even if they are stationary per definition, shocks will have a very long impact on the stock's prices.

5.3 Normal Distribution of the Residuals

5.3.1 Jarque-Bera test

The table below shows 5 of the Jarque-Bera values when testing if the residuals are normally distributed. As seen, all of the values are very high, indicating that the residuals are not normally distributed when dealing with an AR(1) model.

	Jarque-Bera	**Probability**
ABB	43028,43	0,0000
Alfa Laval	1914,04	0,0000
Assa Abloy	131,94	0,0000
Astra Zeneca	329,03	0,0000
Atlas Copco	206,35	0,0000
H_0 Rejects:		**30**

See table 6 in appendix.

The last row, "H_0 Rejects" tells how many times we reject the null hypothesis (out of 30).

5.4 Correlation of the Residuals

When using the two different tests of serial correlation we get the results shown below. Both the Ljung-Box Q-stat and Breusch-Godfrey test indicate that we experience autocorrelation for about one third to half of the stocks. Q = # indicates what lag we are looking at in the correlogram.

	Ljung-Box Q-stat			Breusch-Godfrey Serial Correlation		
	q = 2	q = 8	q = 24	1 lag	2 lags	3 lags
ABB	0,035	0,028	0,000	0,097	0,087	0,050
Alfa Laval	0,002	0,179	0,085	0,116	0,007	0,019
Assa Abloy	0,002	0,002	0,128	0,005	0,005	0,011
Astra Zeneca	0,002	0,000	0,000	0,003	0,009	0,002
Atlas Copco	0,009	0,108	0,043	0,011	0,029	0,042
H_0 Rejects:	**17**	**14**	**16**	**10**	**13**	**15**

See table 7 in appendix.

One reason for this would be the data manipulation we have done on the data; since we have transformed our daily data into weekly we introduce a smoothening effect on the data. It may also be due to a model specification error where we may need to include more variables (*Gujarati, 2006, pp.430-431*).

5.5 Heteroskedasticity

When we have a look at the squared residuals we observe that only a few of the squared residuals are above 5 %, indicating that the data experiences heteroskedasticity. The ARCH LM test provides similar results, and only a handful of the stocks accept the null hypothesis of homoskedasticity. Q = # indicates what lag we are observing in the correlogram.

	Squared Residuals			ARCH LM		
	Q = 2	Q = 8	Q = 24	1 lag	2 lags	3 lags
ABB	0,000	0,000	0,000	0,188	0,000	0,000
Alfa Laval	0,004	0,042	0,537	0,149	0,021	0,050
Assa Abloy	0,000	0,000	0,000	0,000	0,000	0,000
Astra Zeneca	0,001	0,000	0,000	0,001	0,004	0,000
Atlas Copco	0,000	0,000	0,000	0,001	0,000	0,000
H_0 Rejects:	**25**	**28**	**29**	**22**	**25**	**25**

See table 8 in appendix.

5.6 Generalised Autoregressive Conditional Heteroskedasticity

The table below shows the probability values from the normal correlogram and the one with the residuals squared as well as for the ARCH LM Test.

	Correlogram			Corr. Squared Residuals			ARCH LM Test		
	Q = 2	Q = 8	Q = 24	Q = 2	Q = 8	Q = 24	1 Lag	2 Lags	3 Lags
ABB	0,228	0,215	0,233	0,730	0,982	0,011	0,733	0,943	0,977
Alfa Laval	0,002	0,159	0,070	0,003	0,046	0,540	0,041	0,020	0,048
Assa Abloy	0,018	0,034	0,499	0,467	0,778	0,998	0,479	0,759	0,584
Astra Zeneca	0,028	0,001	0,000	0,410	0,420	0,882	0,617	0,712	0,692
Atlas Copco	0,034	0,647	0,245	0,416	0,387	0,334	0,912	0,719	0,559
H_0 Rejects:	**12**	**10**	**10**	**6**	**7**	**7**	**4**	**5**	**7**

See table 9 in appendix.

5.7 Differenced series

The table below shows the results of when we have used a differenced series and a GARCH(1,1) model. The columns are the same as of the GARCH(1,1) in the previous section.

	Correlogram			Corr. Squared Residuals			ARCH LM Test		
	Q = 2	Q = 8	Q = 24	Q = 2	Q = 8	Q = 24	1 Lag	2 Lags	3 Lags
ABB	0,127	0,134	0,117	0,888	0,990	0,029	0,899	0,990	0,992
Alfa Laval	0,184	0,856	0,439	0,540	0,983	0,998	0,616	0,833	0,944
Assa Abloy	0,607	0,191	0,697	0,264	0,651	0,998	0,289	0,529	0,422
Astra Zeneca	0,429	0,005	0,005	0,459	0,420	0,848	0,864	0,766	0,767
Atlas Copco	0,436	0,991	0,447	0,449	0,664	0,490	0,617	0,747	0,732
H_0 Rejects:	**3**	**6**	**6**	**0**	**1**	**1**	**0**	**0**	**0**

See table 10 in appendix.

5.8 Strategy evaluation

Our winner- and loser portfolios consist of the five best-/worst performing stocks from the previous period. These are then bought and held for the subsequent period.

The table below shows how the different strategies have performed during our different holding periods. The contrarian portfolio is made up of going short in the winner portfolio and long in the loser portfolio (Loser – Winner). The momentum portfolio does the opposite (long in winner, short in loser). The market is the buy-and-hold strategy.

The column t-stat is the test statistic of the hypothesis test that the mean return is zero . t-statm on the other hand tests whether the mean return is different from the return of the market portfolio.

Rank period (Months)	**Portfolio**	**Mean**	**Std.dev**	**(t-stat)**	**(t-statm)**	**Sharpe**
1	Winner	0,58%	7,95%	0,768	0,319	0,042
	Loser	0,32%	9,77%	0,343	- 0,023	0,008
	Momentum	0,26%	8,04%	0,343	- 0,101	0,003
	Contrarian	-0,26%	8,04%	- 0,343	- 0,787	- 0,062
	Market	-0,34%	6,87%			- 0,084
3	Winner	3,79%	13,36%	2,966	2,086	0,228
	Loser	-0,76%	17,22%	- 0,436	- 1,143	- 0,087
	Momentum	4,55%	13,44%	3,538	2,664	0,283
	Contrarian	-4,55%	13,44%	- 3,538	- 4,412	- 0,394
	Market	-1,13%	12,37%			- 0,151
6	Winner	5,78%	22,01%	2,718	1,717	0,193
	Loser	-1,00%	27,64%	- 0,373	-1,171	- 0,092
	Momentum	6,78%	21,27%	3,298	2,262	0,247
	Contrarian	-6,78%	21,27%	- 3,298	-4,334	- 0,391
	Market	-2,13%	19,60%			- 0,187
36	Winner	22,81%	57,51%	2,413	- 0,380	0,232
	Loser	27,02%	43,61%	3,768	0,086	0,403
	Momentum	-4,20%	32,34%	- 0,791	- 5,757	- 0,422
	Contrarian	4,20%	32,34%	0,791	- 4,176	- 0,162
	Market	26,40%	37,59%			0,451

6 Discussion

In the following section we will discuss the results from our empirical analysis.

6.1 Discussion about the Unit root tests

Based on the modified Perron testing procedure, all but one stock (Telia) seems to contain a unit root. Most of them make it through all five steps, except for five of the 30 stocks analysed.

- Assa Abloy and Swedbank stop at step #2 indicating that $\rho_c^* = \gamma_c = 0$ is rejected when using the empirical distribution. However, when using the normal distribution instead, the calculated f-statistic is in the right-hand tail indicating the presence of a unit root. Swedbank was the only stock which required more than one lag when optimizing the SIC values, EViews included 13 lags in this case.
- Telia stops at step #3 and thus does not seem to include a unit root when we have a drift term included.
- Lundin and Securitas stop at step #4 indicating that $\rho_b^* = \mu_b = 0$ is rejected when using the empirical distribution. However, for the normal distribution the values are both positive and thus well above the negative critical value.

All of the coefficients of the autoregressive coefficients (with the possible exception of Telia) are found to be less than one which indicates that the time series are stationary, but very close to the unit root. A problem arising when one does not difference a series which contains a unit root are serious (e.g. increasing variance), whilst if one differences a stationary series the only loss is in efficiency (*Kennedy, 2009, pp.301-313*).

Maddala and Kim (*1998, p.146*) argue that a much higher critical level than the 5% which is normally used should be employed since the unit root tests have poor power, making it hard to distinguish whether a test actually supports or is against the null hypothesis when the values are close. The KPSS test requires a good estimate of the long-run variance in order to perform well, as noted by Carrion-i-Silvestre and Sanso (*2006*).

Although all of the tests suggest that $|\rho| < 1$, Kennedy (*2009, p.309*) argues for differencing the data either way since the loss in efficiency is a fair price to pay. Using a higher critical level than five percent make the results even more equivocal. Balvers, Wu and Gilliland (*2000*) argues for the complete opposite, that since mean reversion is very slow and is only picked up over long time horizons one should only difference the data if absolutely needed.

When we conducted the tests discussed below we have kept ourselves to using the original non-differenced data but have kept Kennedy's discussion in mind.

6.1.1 Discussion about the ARMA model selection

The results from the ARMA model selection analysis shows strong support of using an autoregressive model of order 1, AR(1). Although the ARMA(1,1) and AR(2) models are sometimes preferred over AR(1), they often show tendencies of including insignificant terms, something which the AR(1) model does not.

In many of the cases the constant is often found to be insignificant. Kennedy (*2008, p.126*) recommends including it either way since it does little harm and helps to avoid potential problems. Thus we adhere to this recommendation, and use a AR(1) with a drift term included when performing our tests.

6.1.2 Normality discussion

The Jarque-Bera test indicate that the residuals from the AR(1) model are not normally distributed. When dealing with a linear regression model and this is the case, the OLS estimator is still consistent and the asymptotic normality still holds. However it is an indication that there might be something wrong with the model and that it might has to be transformed in order for the normal distribution to hold (*Verbeek, 2008, p.195*).

6.1.3 Autocorrelation discussion

One way in which we can get rid of this serial correlation would be to first-difference the data. However, as mentioned previously this will result in loss of information. What we can do is to either find a better model which helps us get rid of the autocorrelation, or we can difference the series. Another remedial measure would be to use the heteroskedasticity and autocorrelation consistent (HAC) covariance matrices, the opportunity cost of this will be that we lose efficiency, and the OLS estimators are no longer the best linear unbiased estimators (BLUE) (*Gujarati, 2006, pp.431-432*).

6.1.4 Heteroskedasticity discussion

The results from the heteroskedasticity analysis show that the data does not seem to follow a constant variance and thus using an assumption of homoskedasticity seems ignorant. These nonspherical disturbances have the effect of us not being able to rely on the inference and in order to address this problem (as well as the problem with autocorrelation) we have used the HAC variance-covariance matrices (*Gujarati, 2006, pp.431-432; Kennedy, 2009, pp.112-136*).

6.1.5 GARCH discussion

The GARCH(1,1) model shows much better values than the original AR(1) model based on homoskedasticity. When we did the original Ljung-Box test more than half of the time series were correlated, whilst the GARCH-model only shows 12 as being significant (4 is we use a significance level of 1 percent).

We observe the same thing when examining the squared residuals' Q-values and the probabilities from the ARCH LM test. Previously most of the time series exhibited heteroskedasticity whilst after incorporating the GARCH(1,1) only a handful shows signs of this behavior.

6.1.6 Differenced GARCH discussion

Based on the previous results such as the possibility of an incorrectly specified model, the high amounts of autocorrelation and the problem with heteroskedasticity we found it appropriate to try and difference the model. As we have mentioned previously the cost of differencing the data is a loss of information and thus efficiency (*Kennedy, 2009, p.309*), but due to the amount of econometrical problems it seems necessary.

After differencing the regressand there is a dramatic decrease in the amount of problems, as seen in table 10 in the appendix. There are still a handful of series which suffer from autocorrelation, but it is much less compared to the dozen series beforehand. When observing the squared residuals of the correlograms only two of the time series show significant Q-values at a small amount of lags. This indicates that we no longer have a problem with heteroskedasticity.

6.1.7 Mean reversion discussion

Based on the extensive testing above we have found that the time series do show some signs of mean reversion. However, this is very slow and we observe problems with both autocorrelation and changing variance. Using a differenced time series with a generalized autoregressive conditional heteroskedasticity model we do seem to get rid of a majority of these complications.

If mean reversion were to hold this would mean that one can use a contrarian strategy since the stock prices would move towards the mean. Otherwise one could use a momentum strategy in order to buy (short sell) stocks which have performed well (badly) previously. If the stock prices follow a random walk neither of these strategies would hold and we would not be able to support mean reversion. We will discuss this in the next section.

6.2 Trading strategies discussion

When using the strategy of only buying winners, we obtain positive returns for all periods and statistical significance for our 3- , 6- and 36 month periods on a 5% test-level. At first glance, this would indicate that there is a momentum effect for the winning stocks. But when looking a bit closer on the respective periods, a few questions arise.

While both our 1 month investments yields an average return of 0.58% and 0.32% respectively, one has to bear in mind that the results are neither statistically significant, nor do our evaluations take relevant aspects such as transaction costs or tax effects into consideration. Especially since the procedure is repeated each month. With this in mind, we tend to agree with Conrad et al (*1997*) that the inclusion of these factors would nullify the positive returns for our short investments.

The results of our 3 month portfolios yields an average return of 3.79% , beating the market by 4,92% and shows a strong statistical significance on the 5 %-level. Even a winner-loser portfolio shows statistical significance on this level and is also beating the market. This is comparable to the results documented by the likes of Rouwenhorst (*1998*) and others. It should be mentioned though, that they based their portfolio assets on altered formation- and holding periods, something we chose not to. This could be one reason to why they obtain different returns. The same momentum effect holds partly for the 6 month zero-investment portfolios, though they are not statistically different from the market index. In line with previous findings, the momentum strategy appears to be more profitable during medium-term horizons, peaking at 3 months (see Jegadeesh and Titman (*1993*) and others). Its returns are thereafter decaying compared to the market as we increase the holding period.

Our loser portfolios are only profitable during our shortest- (1 month) and longest (36 months) investment horizons and only significant on the latter. The returns on 3- and 6 months are both negative. It seems as if the contrarian effect does not seem to hold for any of the stocks in a medium-term period, and only for the losing stocks in short-, and long-term periods. This is in contrast to the findings of Jegadeesh (1991) and Lehmann (1990) who both documented positive returns in 1 month for their contrarian strategy. Only on a 36 month period the contrarian strategy earns positive returns, which is similar to the findings of Du Bondt and Thaler (1985). However, this strategy fails to outperform the OMXS30 index since the winning stocks are also profitable. The aforementioned gives further proof of the momentum strategy being the best alternative on medium-term horizons.

The market is characterized by negative returns and thus negative Sharpe-ratios for all but the 36-month period where the ratio is higher than the other strategies. The negative ratios suggest that the investor receives negative returns for the risk taken. In other words, the investor is better off investing in the riskless asset. Normally, this would lead the investor to sell short, but in order to keep our test somewhat narrow, we exclude this option in our evaluation.

In comparison to the market, the Sharpe-ratios for all strategies except the 3- and 6 month loser-strategy suggest that they are better investment alternatives. For our short investment period they are however rather low and we would thereby have to agree with the argument used by advocates of the EMH such as Fama and French (*1988*); that in order to earn higher returns (especially in the short run), the investor has to take on additional risk.

The fact that our medium-term strategies both show such high Sharpe-ratios also indicates that these are the most profitable strategy even after adjusting for risk. The same can be said about the winner-loser portfolios during the same periods. While these ratios are not the highest, one has to remember the difference in formation-, and holding-periods.

On a 36 month horizon, investing in the market index appears to be the equivalent to a loser portfolio. While the market index shows a lower average return than the losing strategy, its Sharpe-ratio is higher. This would suggest that the market gets more efficient as the time goes.

7 Conclusion

A short summary of what we have established during our thesis.

7.1 Mean Reversion

The first part of the thesis has analysed whether the stocks on the Stockholm stock exchange exhibits tendencies of mean reversion. The previous research has reached different conclusions, some claim that mean reversion is observed, whilst others claim the opposite.

In our study we have found that when using a normal AR(1) model there is a tendency of mean reversion occurring in the long run. However, a problem with this is that the inference is biased due to autocorrelation and heteroskedasticity. In order to accommodate for this we have used HAC robust errors.

We have also used an approach where we analyse the GARCH(1,1) model. This method is more efficient than using the HAC errors, but some of the AR(1) coefficients are now very close to unity. The model only shows limited signs of being heteroskedastic and autocorrelated, which is much better than the original AR(1) model. The differenced GARCH(1,1) model provides much better results since it does not seem to be heteroskedastic and very few time series now show tendencies of being autocorrelated.

7.2 Trading Strategies

Based on the rather inconclusive results from the unit root tests, we find it hard to differ between whether the stock prices exhibit a random walk or if they simply are stationary with a very long memory. We thus use the trading strategies and analyse whether they can create abnormal profits. Our findings were to some extent in line with the previous research mainly conducted in the U.S. stock market.

Though an efficient market rejects the idea of stock price predictability, the losing portfolios were profitable and beating the market on both a 1- and 36-month investment period. Similarly, the winning portfolios were profitable on all horizons, beating the market on all but the 36-month period. One could argue that they are profitable considering that they earn positive returns while the market is declining for all but the 36-month horizon.

On the 3- and 6-month horizon, a zero-investment momentum portfolio on average outperformed the market and showed statistical significance on a 5% test-level. This would make a momentum-strategy profitable on the medium-term horizons.

The returns from our different portfolios thus suggest that the strategies do not necessarily contradict one another. It appears as if there is a simultaneous momentum effect for winning stocks and a contrarian effect for the losing stocks, at least on longer horizons.

Despite the econometrical analysis showing only a small indication of stock price predictability, the significant results of our medium-term winner-strategy and the long-term results of our loser-strategy would suggest that the market might not be that efficient after all. This raises the question of what factors are behind these mixed results. A possible explanation could be behavioral factors where the market either under- or overreacts to information in the short run. It could also be due to our choice of data or stock selection which may also explain the differences to earlier studies.

The fact that our data sample incorporates two crises, the aftermaths of the dot-com frenzy and the sub-prime crisis, might also have an impact on our results. This might even help to decrease the positive returns why studies excluding these episodes could increase the reliability of the tests.

7.3 Suggestions for future research

We have found that the stocks on the Swedish OMX S30 index either have extremely long memory when subjected to shocks, or that they exhibit random walk behavior. However, which of these two hypotheses that is the correct one is still uncertain.

We would thus suggest further research within the field of the efficient market hypothesis. One suggestion would be to analyze whether the size of the market makes an impact. This could be done by analyzing the small, mid and large cap at Stockholmsbörsen, or another stock exchange.

Many argue that the trends in stock prices are only detectable during long periods of time, but this does not explain the profitability of these short- and medium-term strategies. Neither does it explain how the two strategies we have looked at can yield positive returns during the same period. Deeper studies in the field of behavioral finance could therefore be of interest.

We also believe that quick technological advances help bring the markets more efficient, why studies in developing markets, not as efficient as the U.S and central Europe, would be of great interest to investigate.

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Appendix

Table 1: Unit root test using ADF.

	Observations	Step #1	Step #2	Step #3	Step #4	Step #5
ABB	545	0,805	1,662	0,543	1,100	0,573
Alfa Laval	394	0,426	2,713	0,828	0,293	0,923
Assa Abloy	786	0,243	7,610	-	-	-
Astra Zeneca	556	0,295	3,379	0,209	2,429	0,633
Atlas Copco	1044	0,096	4,979	0,831	0,285	0,961
Atlas Copco B	1044	0,123	4,617	0,803	0,364	0,954
Boliden	552	0,811	2,260	0,513	1,227	0,498
Electrolux	1044	0,129	4,613	0,771	0,457	0,927
Ericsson	1044	0,910	1,524	0,447	1,395	0,761
Getinge	863	0,484	2,568	0,671	0,735	0,988
HM	1044	0,888	2,640	0,192	2,513	0,997
Investor	1044	0,457	2,559	0,567	1,028	0,852
Lundin	430	0,955	3,075	0,149	5,234	-
MTG	637	0,637	2,134	0,270	2,086	0,871
Nokia	130	0,223	3,894	0,850	0,226	0,218
Nordea	625	0,334	3,100	0,336	1,795	0,830
Sandvik	1044	0,156	4,369	0,560	2,247	0,948
SCA	1044	0,077	5,270	0,507	1,206	0,852
Scania	713	0,447	2,618	0,579	0,994	0,841
SEB	1044	0,532	2,261	0,557	1,059	0,681
Securitas	960	0,939	2,994	0,144	5,157	-
SHB	1044	0,694	1,679	0,751	0,512	0,938
Skanska	1044	0,236	3,860	0,700	0,657	0,792
SKF	1044	0,060	5,809	0,784	0,419	0,876
SSAB	1044	0,489	2,435	0,804	0,363	0,927
Swedbank	756	0,553	68,005	-	-	-
Swedish Match	707	0,326	3,149	0,867	3,261	0,996
Tele2	707	0,350	3,615	0,077	3,616	0,859
TeliaSonera	494	0,118	5,775	0,046	-	-
Volvo	1044	0,363	2,969	0,666	0,751	0,888
Critical Value		0,05	6.30	0,05	4.61	0,05

Table 2: Phillips-Perron test

	Trend & Constant		Constant		None	
	t-stat	p-value	t-stat	p-value	t-stat	p-value
ABB	-1,450	0,845	-1,368	0,599	-0,298	0,578
Alfa Laval	-2,101	0,543	-0,719	0,839	1,198	0,941
Assa Abloy	-2,610	0,276	-3,903	0,002	1,654	0,977
Astra Zeneca	-2,685	0,243	-2,353	0,156	-0,221	0,606
Atlas Copco	-2,947	0,148	-0,669	0,852	1,579	0,972
Atlas Copco B	-2,813	0,193	-0,761	0,829	1,461	0,965
Boliden	-1,707	0,747	-1,718	0,422	-0,501	0,499
Electrolux	-3,068	0,115	-0,939	0,776	1,098	0,930
Ericsson	-1,388	0,864	-1,763	0,399	0,166	0,734
Getinge	-2,146	0,519	-1,212	0,671	1,953	0,988
HM	-1,173	0,915	-2,399	0,142	2,548	0,998
Investor	-2,460	0,348	-1,520	0,523	0,573	0,840
Lundin	-0,785	0,965	-2,185	0,212	1,304	0,952
MTG	-2,062	0,566	-2,119	0,237	0,644	0,855
Nokia	-2,766	0,213	-0,630	0,859	-1,244	0,196
Nordea	-2,403	0,378	-1,789	0,386	0,592	0,844
Sandvik	-2,741	0,220	-1,473	0,547	1,252	0,947
SCA	-3,213	0,082	-1,493	0,537	0,683	0,863
Scania	-2,377	0,391	-1,462	0,553	0,556	0,836
SEB	-2,460	0,348	-1,634	0,465	-0,075	0,658
Securitas	-1,125	0,923	-2,224	0,198	1,392	0,959
SHB	-2,032	0,583	-1,073	0,728	1,056	0,924
Skanska	-2,741	0,220	-1,146	0,699	0,376	0,793
SKF	-3,233	0,079	-0,847	0,805	0,814	0,888
SSAB	-2,370	0,395	-0,921	0,782	0,987	0,915
Swedbank	-1,869	0,670	-2,306	0,170	0,190	0,741
Swedish Match	-2,796	0,199	-0,534	0,882	2,589	0,998
Tele2	-2,487	0,335	-2,704	0,074	0,642	0,855
TeliaSonera	-3,002	0,133	-2,841	0,053	-0,731	0,400
Volvo	-2,586	0,287	-1,263	0,648	0,775	0,881

Table 3: KPSS-test

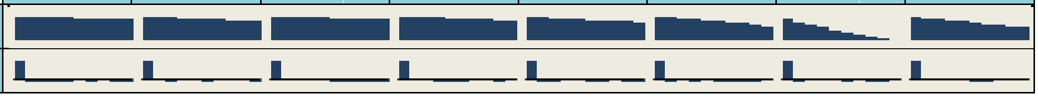
	Trend & Constant		Constant	
	Bandwidth	Test statistic	Bandwidth	Test statistic
ABB	18	0,575	18	0,614
Alfa Laval	16	0,274	16	2,134
Assa Abloy	22	0,656	22	1,868
Astra Zeneca	18	0,116	18	0,709
Atlas Copco	25	0,199	25	3,751
Atlas Copco B	25	0,218	25	3,687
Boliden	18	0,418	18	0,421
Electrolux	25	0,387	25	3,572
Ericsson	25	0,648	25	1,497
Getinge	23	0,264	23	3,381
HM	25	0,911	25	3,672
Investor	25	0,359	25	2,850
Lundin	16	0,628	16	1,899
MTG	21	0,173	21	0,875
Nokia	9	0,135	9	1,270

	Trend & Constant		Constant	
	Bandwidth	Test statistic	Bandwidth	Test statistic
Nordea	21	0,236	21	1,555
Sandvik	25	0,259	25	3,535
SCA	24	0,421	25	3,658
Scania	22	0,316	22	1,920
SEB	25	0,244	25	2,708
Securitas	24	0,864	24	2,861
SHB	25	0,534	25	3,490
Skanska	25	0,201	25	2,804
SKF	25	0,372	25	3,465
SSAB	25	0,263	25	3,212
Swedbank	22	0,302	22	0,634
Swedish Match	22	0,247	22	3,086
Tele2	22	0,320	22	0,595
TeliaSonera	17	0,364	17	0,434
Volvo	25	0,235	25	3,313

Table 4: ARMA models

	ABB	Alfa Laval	Assa Abloy	Astra Zeneca	Atlas Copco	Atlas Copco B	Boliden	Electrolux
AFC								
PACF								

	Ericsson	Getinge	HM	Investor	Lundin	MTG	Nokia	Nordea
AFC								
PACF								



	Sandvik	SCA	Scania	SEB	Securitas	SHB	Skanska	SKF
AFC								
PACF								

	SSAB	Swedbank	Swedish Match	Tele2	TeliaSonera	Volvo
AFC						
PACF						

Table 5: ARMA models – information criteria

Model:	$y_t = \delta + \rho y_{t-1} + \varepsilon_t$			$y_t = \delta + \rho y_{t-1} + \varepsilon_t + \theta\varepsilon_{t-1}$			
	AIC	SIC	AR Root	$P_{MA(1)}$	AIC	SIC	AR Root
ABB	-2,057	-2,041	0,992	0,064	-2,059	-2,035	0,993
Alfa Laval	-2,872	-2,852	0,996	0,032	-2,876	-2,845	0,997
Assa Abloy	-3,135	-3,123	0,992	0,002	-3,143	-3,126	0,993
Astra Zeneca	-3,545	-3,530	0,977	0,004	-3,557	-3,534	0,983
Atlas Copco	-3,193	-3,183	0,999	0,008	-3,197	-3,183	0,999
Atlas Copco B	-3,157	-3,147	0,998	0,006	-3,162	-3,147	0,999
Boliden	-4,869	-4,854	0,994	0,017	-4,877	-4,854	0,993
Electrolux	-3,117	-3,107	0,998	0,177	-3,116	-3,102	0,998
Ericsson	-2,588	-2,578	0,996	0,137	-2,588	-2,574	0,996
Getinge	-3,635	-3,624	0,998	0,354	-3,634	-3,617	0,998
HM	-3,307	-3,297	0,998	0,012	-3,310	-3,296	0,998
Investor	-3,341	-3,332	0,996	0,796	-3,340	-3,325	0,996
Lundin	-2,579	-2,560	0,993	0,089	-2,581	-2,552	0,994
MTG	-2,461	-2,447	0,991	0,953	-2,458	-2,437	0,991
Nokia	-2,820	-2,776	0,990	0,836	-2,805	-2,738	0,989
Nordea	-3,281	-3,267	0,989	0,048	-3,284	-3,263	0,990
Sandvik	-3,359	-3,349	0,997	0,003	-3,365	-3,350	0,997
SCA	-3,540	-3,531	0,996	0,383	-3,539	-3,525	0,996
Scania	-3,292	-3,279	0,994	0,318	-3,290	-3,271	0,993
SEB	-2,489	-2,479	0,996	0,922	-2,487	-2,473	0,996
Securitas	-3,342	-3,332	0,997	0,000	-3,354	-3,339	0,997
SHB	-3,258	-3,249	0,998	0,374	-3,257	-3,243	0,998
Skanska	-3,164	-3,154	0,997	0,154	-3,164	-3,150	0,997
SKF	-3,129	-3,119	0,998	0,122	-3,129	-3,115	0,998
SSAB	-3,023	-3,014	0,998	0,022	-3,026	-3,012	0,999
Swedbank	-3,000	-2,987	0,991	0,155	-3,000	-2,982	0,992
Swedish Match	-4,008	-3,995	0,999	0,000	-4,020	-4,000	0,999
Tele2	-2,849	-2,836	0,987	0,642	-2,846	-2,827	0,988
TeliaSonera	-3,327	-3,310	0,976	0,249	-3,325	-3,300	0,978
Volvo	-3,219	-3,209	0,997	0,242	-3,219	-3,204	0,998

Model: $y_t = \delta + \rho_1 y_{t-1} + \rho_2 y_{t-2}$

	$P_{AR(2)}$	AIC	SIC	AR Root 1	AR Root 2
ABB	0,098	-2,056	-2,033	0,993	-0,072
Alfa Laval	0,117	-2,872	-2,841	0,997	-0,080
Assa Abloy	0,006	-3,143	-3,125	0,992	-0,099
Astra Zeneca	0,003	-3,562	-3,538	0,982	-0,129
Atlas Copco	0,011	-3,196	-3,182	0,999	-0,079
Atlas Copco B	0,013	-3,160	-3,146	0,999	-0,077
Boliden	0,008	-4,877	-4,853	0,993	0,113
Electrolux	0,175	-3,116	-3,102	0,998	-0,042
Ericsson	0,104	-2,588	-2,573	0,996	0,051
Getinge	0,384	-3,634	-3,618	0,998	-0,030
HM	0,020	-3,309	-3,295	0,998	-0,072
Investor	0,795	-3,339	-3,325	0,996	0,008
Lundin	0,099	-2,587	-2,559	0,993	-0,080
MTG	0,944	-2,460	-2,439	0,990	0,003
Nokia	0,854	-2,803	-2,736	0,989	0,017
Nordea	0,061	-3,282	-3,261	0,990	-0,076
Sandvik	0,004	-3,364	-3,349	0,997	-0,088
SCA	0,410	-3,538	-3,524	0,996	-0,026
Scania	0,298	-3,289	-3,270	0,993	0,039
SEB	0,909	-2,486	-2,472	0,996	-0,004
Securitas	0,000	-3,354	-3,338	0,997	-0,115
SHB	0,325	-3,257	-3,242	0,998	-0,031
Skanska	0,160	-3,163	-3,149	0,997	-0,044
SKF	0,137	-3,131	-3,117	0,998	-0,046
SSAB	0,019	-3,026	-3,012	0,999	-0,073
Swedbank	0,096	-3,000	-2,981	0,992	-0,061
Swedish Match	0,004	-4,016	-3,996	0,999	-0,109
Tele2	0,650	-2,845	-2,825	0,987	-0,017
TeliaSonera	0,268	-3,325	-3,299	0,977	-0,051
Volvo	0,179	-3,218	-3,204	0,998	-0,042

Table 6: Jarque-Bera test of the residuals

	Jarque-Bera	Probability
ABB	43028,43	0,0000
Alfa Laval	1914,04	0,0000
Assa Abloy	131,94	0,0000
Astra Zeneca	329,03	0,0000
Atlas Copco	206,35	0,0000
Atlas Copco B	182,31	0,0000
Boliden	309,21	0,0000
Electrolux	368,79	0,0000
Ericsson	828,15	0,0000
Getinge	181,90	0,0000
HM	1147,88	0,0000
Investor	1800,22	0,0000
Lundin	371,63	0,0000
MTG	324,69	0,0000
Nokia	9,84	0,0073
Nordea	1033,84	0,0000
Sandvik	337,07	0,0000
SCA	1211,07	0,0000
Scania	443,50	0,0000
SEB	21782,67	0,0000
Securitas	214,88	0,0000
SHB	6257,31	0,0000
Skanska	861,39	0,0000
SKF	227,32	0,0000
SSAB	837,28	0,0000
Swedbank	2149,06	0,0000
Swedish Match	134,16	0,0000
Tele2	224,04	0,0000
TeliaSonera	95,89	0,0000
Volvo	429,73	0,0000

Table 7: Serial correlation tests of the residuals

	Ljung-Box Q-stat			Breusch-Godfrey Serial Correlation		
	q = 2	q = 8	q = 24	1 lag	2 lags	3 lags
ABB	0,035	0,028	0,000	0,097	0,087	0,050
Alfa Laval	0,002	0,179	0,085	0,116	0,007	0,019
Assa Abloy	0,002	0,002	0,128	0,005	0,005	0,011
Astra Zeneca	0,002	0,000	0,000	0,003	0,009	0,002
Atlas Copco	0,009	0,108	0,043	0,011	0,029	0,042
Atlas Copco B	0,005	0,093	0,155	0,013	0,014	0,029
Boliden	0,003	0,000	0,003	0,008	0,015	0,038
Electrolux	0,175	0,277	0,125	0,176	0,400	0,373
Ericsson	0,022	0,260	0,022	0,104	0,080	0,129
Getinge	0,243	0,618	0,487	0,382	0,502	0,708
HM	0,014	0,125	0,274	0,020	0,041	0,021
Investor	0,768	0,014	0,036	0,794	0,957	0,967
Lundin	0,096	0,147	0,470	0,097	0,253	0,326
MTG	0,909	0,152	0,394	0,954	0,993	0,307
Nokia	0,388	0,066	0,005	0,862	0,697	0,862
Nordea	0,053	0,003	0,009	0,061	0,132	0,252
Sandvik	0,004	0,093	0,012	0,004	0,015	0,038
SCA	0,247	0,159	0,207	0,410	0,496	0,595
Scania	0,248	0,795	0,289	0,298	0,512	0,647
SEB	0,008	0,000	0,000	0,909	0,030	0,048
Securitas	0,000	0,007	0,071	0,000	0,001	0,002
SHB	0,041	0,000	0,000	0,325	0,131	0,246
Skanska	0,146	0,002	0,000	0,160	0,337	0,004
SKF	0,121	0,381	0,433	0,138	0,288	0,342
SSAB	0,017	0,016	0,013	0,019	0,061	0,030
Swedbank	0,005	0,000	0,000	0,096	0,020	0,041
Swedish Match	0,000	0,005	0,122	0,004	0,000	0,001
Tele2	0,573	0,329	0,326	0,649	0,848	0,571
TeliaSonera	0,261	0,139	0,038	0,260	0,517	0,696
Volvo	0,004	0,000	0,000	0,179	0,020	0,026

Table 8: Heteroskedasticity

	Squared Residuals			ARCH LM		
	Q = 2	Q = 8	Q = 24	1 lag	2 lags	3 lags
ABB	0,000	0,000	0,000	0,188	0,000	0,000
Alfa Laval	0,004	0,042	0,537	0,149	0,021	0,050
Assa Abloy	0,000	0,000	0,000	0,000	0,000	0,000
Astra Zeneca	0,001	0,000	0,000	0,001	0,004	0,000
Atlas Copco	0,000	0,000	0,000	0,001	0,000	0,000
Atlas Copco B	0,000	0,000	0,000	0,002	0,000	0,000
Boliden	0,000	0,000	0,000	0,000	0,000	0,000
Electrolux	0,000	0,000	0,000	0,000	0,000	0,000
Ericsson	0,000	0,000	0,000	0,000	0,000	0,000
Getinge	0,110	0,002	0,000	0,672	0,280	0,063
HM	0,083	0,160	0,000	0,132	0,239	0,080
Investor	0,000	0,000	0,000	0,001	0,000	0,000
Lundin	0,000	0,000	0,000	0,000	0,000	0,000
MTG	0,000	0,000	0,000	0,104	0,000	0,000
Nokia	0,700	0,078	0,013	0,772	0,936	0,986
Nordea	0,000	0,000	0,000	0,004	0,001	0,000
Sandvik	0,000	0,000	0,000	0,000	0,000	0,000
SCA	0,001	0,000	0,000	0,004	0,008	0,021
Scania	0,000	0,000	0,000	0,000	0,000	0,000
SEB	0,000	0,000	0,000	0,000	0,000	0,000
Securitas	0,000	0,000	0,000	0,000	0,000	0,000
SHB	0,000	0,000	0,000	0,010	0,000	0,000
Skanska	0,000	0,000	0,000	0,000	0,000	0,000
SKF	0,000	0,000	0,000	0,002	0,000	0,000
SSAB	0,000	0,000	0,000	0,000	0,000	0,000
Swedbank	0,000	0,000	0,000	0,000	0,000	0,000
Swedish Match	0,249	0,000	0,000	0,248	0,516	0,546
Tele2	0,000	0,000	0,000	0,000	0,000	0,000
TeliaSonera	0,594	0,000	0,001	0,835	0,871	0,024
Volvo	0,000	0,000	0,000	0,000	0,000	0,000

Table 9: Properties of GARCH(1,1) model

	Correlogram			Correlogram - Squared Residuals			ARCH LM Test		
	Q = 2	Q = 8	Q = 24	Q = 2	Q = 8	Q = 24	1 Lag	2 Lags	3 Lags
ABB	0,228	0,215	0,233	0,730	0,982	0,011	0,733	0,943	0,977
Alfa Laval	0,002	0,159	0,070	0,003	0,046	0,540	0,041	0,020	0,048
Assa Abloy	0,018	0,034	0,499	0,467	0,778	0,998	0,479	0,759	0,584
Astra Zeneca	0,028	0,001	0,000	0,410	0,420	0,882	0,617	0,712	0,692
Atlas Copco	0,034	0,647	0,245	0,416	0,387	0,334	0,912	0,719	0,559
Atlas Copco B	0,037	0,673	0,442	0,131	0,245	0,242	0,540	0,310	0,361
Boliden	0,013	0,001	0,003	0,427	0,792	0,683	0,773	0,739	0,899
Electrolux	0,555	0,523	0,194	0,150	0,375	0,435	0,830	0,362	0,270
Ericsson	0,082	0,123	0,031	0,431	0,714	0,998	0,578	0,732	0,721
Getinge	0,263	0,855	0,619	0,493	0,826	0,716	0,904	0,788	0,887
HM	0,055	0,611	0,856	0,343	0,768	0,973	0,442	0,637	0,793
Investor	0,265	0,123	0,651	0,598	0,994	1,000	0,652	0,874	0,957
Lundin	0,244	0,814	0,966	0,209	0,105	0,512	0,356	0,476	0,647
MTG	0,387	0,315	0,638	0,221	0,867	0,957	0,877	0,473	0,670
Nokia	0,102	0,113	0,000	0,000	0,001	0,000	0,251	0,001	0,003
Nordea	0,221	0,667	0,622	0,195	0,753	0,831	0,201	0,436	0,405
Sandvik	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
SCA	0,475	0,218	0,244	0,582	0,509	0,142	0,602	0,858	0,254
Scania	0,063	0,652	0,671	0,791	0,920	0,974	0,884	0,962	0,985
SEB	0,195	0,018	0,028	0,714	0,993	0,894	0,717	0,933	0,864
Securitas	0,005	0,056	0,169	0,014	0,000	0,000	0,709	0,050	0,001
SHB	0,036	0,000	0,000	0,000	0,000	0,000	0,014	0,000	0,000
Skanska	0,291	0,022	0,077	0,586	0,429	0,871	0,616	0,860	0,957
SKF	0,220	0,832	0,761	0,435	0,760	0,954	0,637	0,740	0,877
SSAB	0,406	0,503	0,247	0,432	0,955	0,845	0,672	0,739	0,733
Swedbank	0,040	0,018	0,001	0,481	0,821	0,969	0,910	0,786	0,894
Swedish Match	0,000	0,000	0,000	0,000	0,000	0,000	0,001	0,002	0,004
Tele2	0,740	0,091	0,060	0,372	0,888	0,718	0,879	0,683	0,551
TeliaSonera	0,238	0,127	0,035	0,632	0,000	0,001	0,951	0,891	0,025
Volvo	0,023	0,015	0,116	0,492	0,291	0,182	0,529	0,780	0,207

Table 10: Properties of differenced GARCH(1,1) model

	Correlogram			Corr. Squared Residuals			ARCH LM Test		
	Q = 2	Q = 8	Q = 24	Q = 2	Q = 8	Q = 24	1 Lag	2 Lags	3 Lags
ABB	0,127	0,134	0,117	0,888	0,990	0,029	0,899	0,990	0,992
Alfa Laval	0,184	0,856	0,439	0,540	0,983	0,998	0,616	0,833	0,944
Assa Abloy	0,607	0,191	0,697	0,264	0,651	0,998	0,289	0,529	0,422
Astra Zeneca	0,429	0,005	0,005	0,459	0,420	0,848	0,864	0,766	0,767
Atlas Copco	0,436	0,991	0,447	0,449	0,664	0,490	0,617	0,747	0,732
Atlas Copco B	0,446	0,994	0,611	0,130	0,386	0,321	0,326	0,306	0,446
Boliden	0,021	0,002	0,008	0,364	0,764	0,704	0,770	0,674	0,853
Electrolux	0,829	0,573	0,181	0,155	0,351	0,399	0,850	0,371	0,264
Ericsson	0,127	0,184	0,050	0,413	0,706	0,998	0,533	0,711	0,702
Getinge	0,374	0,899	0,685	0,485	0,840	0,746	0,907	0,782	0,892
HM	0,334	0,921	0,964	0,377	0,813	0,953	0,517	0,671	0,824
Investor	0,318	0,165	0,687	0,599	0,994	1,000	0,658	0,874	0,950
Lundin	0,234	0,637	0,793	0,189	0,101	0,604	0,311	0,447	0,605
MTG	0,440	0,255	0,564	0,347	0,887	0,917	0,926	0,643	0,818
Nokia	0,278	0,050	0,012	0,260	0,205	0,112	0,708	0,586	0,726
Nordea	0,885	0,841	0,794	0,203	0,762	0,905	0,207	0,450	0,430
Sandvik	0,689	0,976	0,302	0,399	0,729	0,617	0,984	0,697	0,805
SCA	0,444	0,270	0,255	0,440	0,479	0,082	0,481	0,741	0,240
Scania	0,654	0,966	0,834	0,894	0,916	0,974	0,956	0,992	0,975
SEB	0,090	0,015	0,024	0,678	0,992	0,958	0,681	0,915	0,860
Securitas	0,343	0,661	0,875	0,201	0,747	0,832	0,631	0,440	0,649
SHB	0,122	0,040	0,008	0,404	0,941	0,744	0,471	0,703	0,812
Skanska	0,426	0,036	0,094	0,672	0,456	0,837	0,714	0,912	0,976
SKF	0,916	0,963	0,840	0,513	0,797	0,952	0,673	0,809	0,910
SSAB	0,366	0,527	0,207	0,434	0,958	0,822	0,669	0,741	0,744
Swedbank	0,259	0,066	0,004	0,497	0,883	0,987	0,946	0,799	0,915
Swedish Match	0,007	0,076	0,256	0,708	0,005	0,193	0,975	0,936	0,713
Tele2	0,782	0,099	0,057	0,336	0,884	0,643	0,876	0,643	0,617
TeliaSonera	0,843	0,520	0,182	0,250	0,822	0,993	0,317	0,513	0,593
Volvo	0,018	0,013	0,115	0,475	0,270	0,173	0,500	0,772	0,189