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# Efficient Market Hypothesis: Testing for Price Predictability on the OMX Stockholm 30 Index


**NEG300, Nationaleconomics, In-depth Course**

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# Abstract

The use of historical information to predict future pricing of equities has been a topic of debate among the financial community for some time. This study examines the issue by testing for statistical significance on lagged price values, utilizing an autoregressive model. In the tests we use data from the OMX Stockholm 30 index.

The study utilizes an autoregressive model (AR) to check two different time frames simultaneously. In part we examine lagged values in the short run whilst also observing lagged values for longer time periods. There are three tests in total, one testing for the 2015-16 period, one for the 2014-16, and finally one for the 2014-15 period.

The test results obtained show that the strong form of EMH does not hold on the OMX Stockholm 30 index due to the finding that there is statistical significance in some of the lagged variables, which implies that historical prices do affect future prices.

# Content

# 1. Introduction

## 1.1 Background

There is a central problem to investing and trading that every participant must (or should) develop a strategy to deal with, and that problem is “What is the price of equities going to be in the future?” Some people like Burton Malkiel (2011) and Eugene Fama (1970) theorize that the equity prices are efficient - that all available information is reflected in the price - and that strategies can be formed to utilize this information. Others like Andrew Lo and Craig MacKinlay (1999) would argue that the equity prices are not efficient enough to properly reflect the available information of the equity, and that any financial strategy must base itself on that premise.

How, and if it is possible, to predict equity indexes and make a profit on them has been an economic hot topic since equity markets have been introduced. Many papers and books have been written arguing the theories for and against the possibility of predicting equity prices.

One of the attempted explanations that has remained popular to this day is the Efficient Market Hypothesis, which has become a major player in discussions of the financial market´s predictability since it was originally conceived by Eugene Fama in 1970 (Malkiel, 2003). The EMH is a theory which argues that financial markets adapt to different kinds of information, and that prices in the market respond to . To which degree the market responds to the information is accounted for in the theory by the presence of three different strength levels; the weak, the semi-strong, and the strong form. In particular, the strong form states that all information, including hidden information, is reflected in the price of the equity (Fama, 1970).

The method used to test the EMH in this study is the econometric model known as autoregressive time series (AR). The reason for using the (AR) model is that it tests a variable against its past values, thereby enabling us to study the presence of information in historic prices. We test two time perspectives simultaneously, a short term (up to 10 days) and a long term (up to 200 days). The reason for using two perspectives is to test a supposition by Fama (1997) that any lag in response of a price change is short lived. It is in response to this that we have created these two time frames.

The data used in our test contains the closing prices of the OMX Stockholm 30 index. The closing prices are used in three tests, two single year tests (2014-15 and 2015-16) and a one double year test (2014-16).

### 1.2 The OMX Stockholm 30 index

OMX AB, a company within the NASDAQ OMX Group, owns the equity index OMX Stockholm 30 Index. The OMX Stockholm 30 Index is a price return index constructed with the objective of creating an index based on a limited number of shares which then develops in close correlation with the equities listed on NASDAQ Stockholm. The primary objective of the Index is to reflect the development of the shares included in the portfolio. The shares included in the index are also listed on NASDAQ Stockholm. OMX Stockholm Index includes the 30 shares which have the largest trading volume calculated in SEK during a control period consisting of six months containing data through the end of November and May (NASDAQ, 2014).

### 1.3 Purpose

The goal of this study is to examine the existence of the strong form of EMH on the OMX Stockholm 30 index. By evaluating the strong form of EMH we aim to add information regarding the presence of historic index prices on future index prices, and also intend to add information to the body of work surrounding the discussion of the theory.

Should it be that EMH in fact is in effect on the OMX Stockholm 30 index, it will have implications on how investors and traders should conduct their respective activities on the index. It would then be critical to create strategies to account for the presence of the EMH, though we will not actually attempt to formulate such strategies ourselves.

### 1.4 Disposition

Following this introduction, there will be a section discussing the two different theories and some of the conflict between them, which includes literature analysis. The third segment provides information on the analysis´ method, the data, and the OMX Stockholm 30. This is then followed by a section detailing our results, before ending with a discussion. References and an appendix are found at the end. The appendix contains three tables displaying the results from our tests.

### 1.5 Summary of the Conclusion

We have tested the strong form of EMH in our study using an autoregressive model with nine lagged variables (AR(9)), which have given us results that enables us to reject the strong form of EMH. These results have yielded enough information to show that historical price information will affect future prices, albeit only conclusively in the short term.

# 2. Theory and Literature Analysis

## 2.1 The Efficient Market Hypothesis

The Efficient Market Hypothesis (EMH) was originally formulated in full by Eugene Fama in 1970. Its core concept can be expressed as follows: Any market in which the price of capital reflects the information available to investors and traders is viewed as efficient. As long as enough traders agree of the security price, the information is sufficiently cheap enough to gather, and the transaction costs can be foreseen, the market will be efficient.

EMH is a theoretical model and true market conditions have "friction variables" that can hinder or strengthen the EMH to some extent. The friction can be caused by transaction fees, the costs of information gathering, or disagreement among traders regarding the price of the security, to make but a few examples. What these frictions actually are in practice differs depending on the time period, for example trading has become cheaper over time with lower transaction fees. With the help of internet technology, more information can spread faster among traders, making it cheaper to gather information. But with the frictions of the market stated above there is not said that the efficiency of the markets would not be true (Fama, 1970).

There are three levels of "strength" the theory can take: The weak form, the semi-strong form, and the strong form. These strength levels indicate how quickly and efficiently the market responds to new information. The weak form argues that prices reflect the available historical prices in the market. The semi-strong form maintains that in addition to historical prices, prices also reflect other publicly available information. The strong form goes one step further and suggests that price, in addition to the above, also changes to reflect hidden and private information (Fama, 1970).

The EMH is often associated with the so-called "random walk", which is a loose concept used in finance to describe the idea that all (or almost all) price changes within a price series are essentially random and unpredictable. This, according to the EMH, is because prices reflect all available information. But since new information is often unpredictable, the price changes will effectively be random. If something can be predicted the price will have already adjusted to it, the theory argues (Malkiel, 2003).

The Random Walk model consists of two hypotheses. The first is the statement that the current price of a security fully reflects available information and implies that successive one-period returns are independent. The second statement is that successive changes are identically distributed. This definition of the random walk model is probably best associated with the strongest form of EMH due to the above assumptions, namely that the current price of the security fully reflects all available information. We can thus interpret the Random Walk model and the EMH to be the following:

$$f\,(p_{j,\ t+1} \mid \Phi_t) = f\,(p_{j,\ t+1}) \qquad [2.1]$$

The model (2.1) is describing that the future price (p) of the security (j) is independent of the information of $\Phi_t$, thereby stating that future price is a random variable and that information is fully reflected in p (Fama, 1970).

As the EMH states that prices reflect the information of the equity, if the equity would be undervalued the buying pressure from buyers would raise the value of the equity and vice versa regarding overvaluation of the equity. In this hypothesis the only movement of the equity would be as a result of new information. As new information is expected to be random the EMH and the Random Walk model become tied together in this particular situation.

The EMH model also traces some of its lineage to the fair game model, which assumes that there would be no risk premium depending on security risks, thereby implying equal expectations of gain or loss.

According to (Fama, 1970) all members of expected such return theories can be described notationally in the following form:

$$E(\acute{p}_{j,\ t+1} \mid \Phi_t) = [\ 1 + E(\acute{r}_{j,\ t+1} \mid \Phi_t)\ ]\ p_{jt} \qquad [2.2]$$

"E is the expected value operator; $p_{jt}$ is the price of security j at time t; $p_{j,\ t+1}$ is the price at $t$+1; $r_{j,\ t+1}$ is the one period percentage return $(p_{j,\ t+1} - p_{jt}) / p_{jt}$; $\Phi_t$ is a general symbol for whatever set of information is assumed to be fully reflected in the price at t; the ´ indicate that $p_{j,\ t+1}$ and $r_{j,\ t+1}$ are random variables at time t." (Fama, 1970, p. 384)

EMH and the Random Walk Theory are closely tied to each other. But evidence of the Random Walk Theory does not imply that EMH does work. Lo & MacKinlay (1999) refers to LeRoy (1973) and Lucas (1978) that the Random Walk model is neither a necessary nor a sufficient condition for rationally determined security prices. Unforecastable prices do not need to imply efficient markets and forecastable prices do not imply inefficient markets.

**2.2 Criticism and Discussion of the EMH**

Over the years since Fama laid out the groundwork in 1970 the EMH has enjoyed a lot of support, but increasingly less so in modern times. It is now considered fairly normal to hold the view that equity markets can at least partially be predicted. Prominent proponents of this view are found among behavioral finance researchers and econometricians, who argue that there are observable patterns in the equity market (Malkiel, 2003). The financial crisis between 2007-2009 has escalated the level of criticism aimed at the theory, though adherents of the theory maintain that faith in the EMH was not responsible for the crisis (Malkiel, 2011).

In Fisher Black´s (1986) basic financial model he uses the term "noise" to describe contrasted information. People either trade on correct information or on noise which they believe is information. Noise trading is essential to the existence of the liquid markets. Otherwise there would be an equilibrium in the equity prices and arbitrage opportunities would not exist. Noise in the market causes market inefficiency and makes them possible.

Black (1986) further argues that if there was no such thing as noise trading there would be very little trading in individual assets. If a person that has particular information about a particular equity would want to trade to make arbitrage there would be no reason to trade because all other traders already knows the price of the equity and thereby arbitrage opportunities would diminish.

Due to the millions of active traders there is clearly arbitrage profits from the equity markets, otherwise the marketplace for trading equity would probably not exist. The existence of financial markets can be a proof of that even if the EMH holds there will always be a mismatch of information and contrasted information among traders, thereby creating arbitrage opportunities among traders.

Sanford Grossman and Joseph Stiglitz (1980) argue that if competitive equilibrium is defined as a situation in which prices are such that all arbitrage profits are eliminated then a competitive economy can not always be in equilibrium. That's because of those who arbitrage would make no return from their costly activity. Furthermore, Lo & MacKinlay (1999) argue that the Random Walk Hypothesis a purely statistical model of returns need not to be satisfied even if prices do fully reflect all available information. At any time there is always investors trading for other reasons other than information for example, investors in need of liquid assets. There is nothing irrational about these investors or inefficient rather than they do not trade the information in the prices of the equities.

The Random Walk model commonly clashes with technical analysis on several points. Technical analysis is based on information collected through historical data and attempts to predict the future based on that information. Random walk advocates on the other hand view that using historical data to predict future price movements is neither feasible nor possible. This conflict can be exemplified by the two books “A Random Walk Down Wall Street” (Malkiel, 2011) and “A Non-Random Walk Down Wall Street” (Lo & MacKinlay, 2001). Malkiel is highly skeptical of technical analysis, going as far as to state that it is the financial equivalent of alchemy: unreliable and unscientific. Major components of his criticism towards it are that it falls prey to the human impulse to see a pattern where there is none, that the schemes for technical analysis tend to only work for a specific given period, and self-defeating in the end. With respect to the third point, he argues that even if a persistent pattern is found over several time periods it would still be rendered irrelevant the when it became common knowledge. Traders and investors would, in his view, simply respond to the pattern by acting in a way that prevents it from occurring, thereby invalidating it (Malkiel, 2011).

Many of Fama´s studies focus on returns in a short window (a few days) around an event with a clear start date. An example of such an event can be an equity split. The daily expected returns are close to zero in a short window consisting of a few days, the study in of a short window for expected returns does in that way not have a big effect on inferences about abnormal returns. The studies focusing on short window returns tend to assume that any lag in response to price is short lived. Thereby strengthening the theory of market efficiency hypothesis that the anomalies are chance results, overreaction to information is about as common as under reaction, and post event continuation of pre-event abnormal returns is about as frequent as post-event reversal. The opposing theories that challenge EMH state historical prices affect future prices and that prices adjust slowly to information. To receive a correct view of price movement one must study price movements over a long period of time (Fama, 1997).

Burton G. Malkiel, an advocate of the EMH, does not argue that market pricing is always perfect. Furthermore, Malkiel (2003) argues that psychological factors can influence security prices and refers to Benjamin Graham (1965) that while equity markets in the short run may be a voting mechanism, in the long run it is a weighting mechanism. True value will win out in the end.

Andrew Lo & Craig MacKinlay (1999) compares the classical version of the EMH to a non-fictional market, the biotechnology market. The argument is that if the biotechnology market is efficient in the classical sense a vaccine such as one against AIDS can never be developed, if it could someone would already have invented it.

Lo & MacKinlay (1999) rejects the random walk model for weekly equity market returns (September 6, 1962, to December 26 1985 NYSE-AMEX index) thus strengthening technical analysis by using a simple volatility-based specification test. Lo & MacKinlay (1999) also states that by rejecting the random walk model does not necessarily imply the inefficiency of equity price formation.

Grossman and Stiglitz (1980) rejects the EMH, arguing that informationally perfect efficient markets are an impossibility on the basis that the returns on gathering information in an efficient market are nil, resulting in that there would be little or no reason to trade so the markets would eventually collapse.

**2.3 Other Theories Regarding Price Predictability**

"Even after three decades of research and literally thousands of journal articles, economists have not yet reached a consensus about whether the markets - particularly financial markets - are efficient or not."

- Lo & MacKinlay (1999)

For a long time, technical chart analysis has been considered an outcast in economic theory and derisively referred to as "voodoo finance" (Lo et al., 2000). However, despite its critics, it is considered by many to be the original form of investment analysis, dating back to the 1800s and it was used before the period of fully disclosed financial information that later formed the fundamental analysis. The oldest incarnation of technical analysis is attributed to Charles H. Dow and his fellow students and is traced back to the late 1890's. Charles H. Dow and his fellow students discovered that the equity market had a trend, that equities as believed earlier did not move independent of each other but rather that the market analyzed ( the current Dow Jones Industrial and Transportation averages) moved more or less unison. This trend movement led to the development of the famous Dow Theory. The Dow Theory is based on trending the movements of the averages, a trending still up to date widely used (Hamilton & Rhea, 2015). One reason for the Dow Theory still remains a popular method for timing the market is that during the first three decades of 20th century it appeared to work. Regardless of whether it worked since then, this early success established a reputation that has endured for decades. William Peter Hamilton the editor of *The Wall Street Journal* after Charles Dow's death 1902 who was the founding editor, wrote a series of editorials in *The*

*Wall Street Journal* and in *Barron's* discussing and forecasting major trends in the U.S. equity market. Hamilton cited Charles Dow's theory of equity market movements as the explicit basis for market predictions (Brown, Goetzmann & Kumar 1998). Hamilton explains the basic outlines of the theory in his 1922 book *The Stock Market Barometer*. The theory presupposes that the market moves in persistent bull and bear trends. By charting past fluctuations in the industrial and transportation indices the analyst can identify the primary market movements according to Hamilton (Brown, Goetzmann & Kumar 1998).

The extent of which the strength of technical analysis as a tool is recognized can be seen in that most major modern financial newspapers relate some part of their index information on technical analysis.

In its true form technical analysis was based on visual pattern recognition, making it an art form to a certain extent, which it also remains to this day. Visual indicators, such as candlesticks and moving averages has been developed and libraries of indicators has formed. Recently a lot of computational automated help has developed and can be found in many trading websites. As technical trading is a visual artform performed by the expert human eye, can we be so bold that we try to question their ability to predict price changes by statistical analysis? Of course, the answer to that question is no, even if we don't find patterns in our tests there is no answer to that an expert technical trader would not do so.

Despite that there are well developed technical regularity libraries containing geometric formations (such as the head and shoulders formation), a large amount of them are of the homegrown kind meaning that the regularities and formations are often subjectively modified. This is, however, also a major weakness when testing for the authenticity of technical analysis, because we can only test the indicators and not the specific traders.

The term technical analysis is a general term containing a diversified number of trading techniques. To break the term down, the main purpose of technical analysis is to identify regularities in time series of prices, regularities which for example can be in found the geometric patterns of candlesticks. Therefore technical analysis is dependent on that there is future information in historical prices. The historical reading of price charts and its formations is one main strifes between fundamental analysts and technical analysts. Lines of research against respective theories are found and it is impossible to conclude which theories fall the closest in line with reality.

So is technical analysis beneficial to the trader? Andrew W. Lo et al (2000) logarithmized technical patterns and find certain technical patterns do provide incremental information. William Brock et al (1992) provide information of two competing explanations for the presence of predictable variation in equity returns which are following, *Market inefficiency*, in which prices take swings from their fundamental values, and *markets are efficient* where the predictable variation can be explained by time-varying equilibrium returns.

In a study William Brock et al (1992) test the most popular trading rules, the moving average-oscillator and trading-range break (resistance and support levels) on the Dow Jones Industrial Average (DJIA) between 1897-1986 and find that technical analysis helps to predict equity price changes.

In other words, the trading profits are not consistent with a random walk. To implement the Random Walk theory of that the actual value of the equity i represented in the price we can implement it to an old economic joke: "An economist and his companion are strolling down the street when they come upon a $100 bill lying on the ground. As the companion reaches down to pick it up, the economist says. Don't bother - if it were a real $100 bill, someone would have already picked it up" (the economist in the quote being a random walk economist)(Lo & MacKinlay, 1999, p. 6).

### 2.4 Relation to this Study

In summary, the EMH is a contested topic, with increasing amounts of criticism being directed towards it (Lo, Andrew W. MacKinlay A. Craig. 1999), (Grossman, Sanford J. Stiglitz, Joseph E. 1980). One reason in particular, mentioned by Malkiel (2011), is the rise of econometric analysis, which has been an important player in raising skeptical voices of the EMH (Malkiel, 2011).

In light of this, we intend to utilize econometric analysis in the form of an autoregressive model in order to study whether the strong form of EMH can be disregarded or not when testing it on the OMX Stockholm 30 Index. The reason for using the OMX Stockholm 30 index is the geographical location of the authors.

# 3. Method and Data

### 3.1 The Autoregressive (AR) Model

The autoregressive model has been selected on the basis that it examines specifically how past instances of a variable affect the current instance (Wooldridge, 2013). This enables us to examine if the historical information contained in the OMX Stockholm 30 index will affect future prices, thereby testing for the strong form of EMH.

The autoregressive model is an econometric time series tool that tests a variable against its past values. If a past value of $t$-j has statistical significance, it implies that it is having an effect on the variable t being analysed. Furthermore, it can be interpreted to mean that if a future value of $t$+1 is analysed, the variable $t+1-j$ will have an effect on $t$+1 ($j$ is interpreted as the lag).

Figure 3.1 Illustration of lags

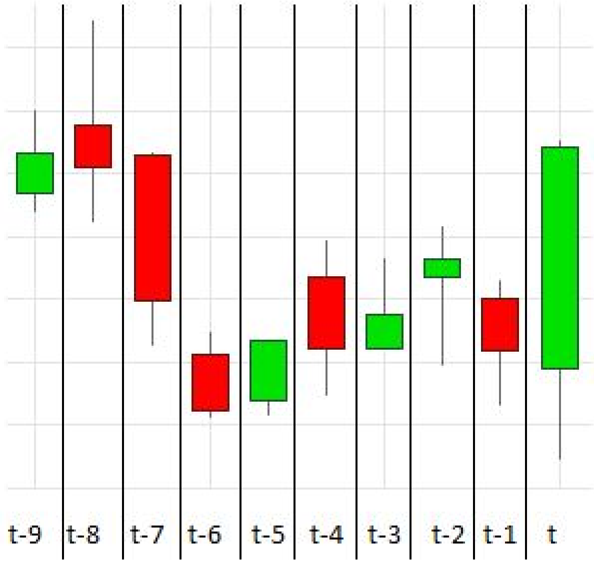


Figure 3.1 by authors, using chart data from Investing on the OMX Stockholm 30. Description of figure [3.1]. The green candles represent bullish closing prices and the red candles represent bearish closing prices. The closing price is read at the end of the body of the candles direction. The figure only illustrates the lags, otherwise the y-axis would contain index points and the x-axis would contain time.

An AR model can test the lagged value of any of the variables in figure 3.1. For instance, if we wish to test the second lag´s significance, the autoregressive model would evaluate all second lags for all possible variables; *t*-7 would be tested against *t*-9, *t*-6 against *t*-8, and so forth. In this case *t*-9 and *t*-8 do not have second lags accounted for in the data, which means that the test cannot be performed on them, causing them to only be used as lags for other variables. Should the test instead evaluate all first lags, *t*-8 would then be observed in the test where it would be tested against *t*-9. *t*-9, however, would still not be included (Wooldridge, 2013). This has been accounted for in our test by adding observations in each of the datasets (discussed in 3.3).

### 3.2 Description of the Test

This study will check for historical correlations between prices on the OMX Stockholm 30 index using an autoregressive model. This is done to determine whether the strongest form of EMH holds for this particular index.

According to the strictest form of EMH, past information will not affect future prices (Malkiel, 2003). As Fama (1970) noted, this is effectively a null hypothesis, meaning that if the ρ-value exceeds the confidence level for an independent variable, it would be a point in favor of the EMH.

The study will test the EMH in its strong form, which will be done by regressing the closing price of OMX Stockholm 30 index on 9 different lagged values of itself. The lags are the following: 1 day, 2 days, 3 days, 4 days, 5 days, 10 days, 50 days, 100 days, and 200 days. This makes it an autoregressive model of the 9th order that takes the following shape:

$$y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \beta_3 y_{t-3} + \beta_4 y_{t-4} + \beta_5 y_{t-5} + \beta_6 y_{t-10} + \beta_7 y_{t-50} + \beta_8 y_{t-100} + \beta_9 y_{t-200} + u_t \quad [3.1]$$

where ($y_t$) is the closing price at time $t$, the independent variables ($y_{t-j}$) are the lags on the closing price where ($j$) represents the lag. ($\beta$) is the economic coefficient of the lags received from the AR. ($u_t$) contains the unobserved variables at time $t$.

For purposes of this test, the value of the constant $\beta_0$ is not relevant to the analysis of whether the strong form of EMH holds true or not. The point of the test is check the statistical and the economical significance of the coefficients $\beta_1$-$\beta_9$.

The EMH´s argument that past prices do not affect future prices can be expressed as follows (Wooldridge, 2013):

$$E(y_t|y_{t-1}, y_{t-2}, y_{t-3}, y_{t-4}, y_{t-5}, y_{t-10}, y_{t-50}, y_{t-100}, y_{t-200}) = E(y_t) \qquad [3.2]$$

The equation (3.2) states that the expected value (E) of y at time t is not affected of past values ($y_{t-j}$), thereby stating that historic prices does not affect current price.

The null hypothesis for the regression is as follows:

$$H_0 = \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = \beta_8 = \beta_9 = 0 \quad [3.3]$$

The test uses a confidence level of 95%; should the ρ-value be larger than 0.05 on any variable, the null hypothesis would be rejected.

We have selected two different time frames for testing the EMH, one shorter time frame and one longer time frame, both defined by this study. The former ranges from the 1-day lag to the 10-day lag, while the latter is tested in the 50-day, 100-day, and 200-day lags. The reason for the study dividing the test into a shorter time frame and a longer time frame is due to the discussions regarding in which time period EMH holds. In our study we test for lags in a short time frame consisting of 1-day lag to 10-day lag. The short lag regressions are tested to find out how EMH works on OMX Stockholm 30 in conclusion with EMH assumption by Fama (1997) where the assumption is that any lag of a price change is short lived.

Both the critics and the advocates of the EMH seem to agree that short lags or as called short windows in the market consisting of a couple of  days have some predictability due to short historical price movements (Fama, 1997).

The second part of the regression is the 50-day, 100-day and 200-day lag. This part of the regression is to test if equity prices adjust slowly to price changes thereby making historical price levels informative. The 50-day, 100-day and 200-day lags are chosen with the intent to examine a longer period of time in contrast with the short window.

By testing for longer lags there is a possibility that we include shorter economic cycles in our model within the period tested. By using the AR(9) regression on the chosen lags we also do not test for historical price information such as specific chart patterns observable by the human eye, such as the head-and-shoulders formation.

As both the critics and the advocates of the EMH seems to agree that the price changes in a short window affect future prices. The argument between the critics and the advocates of the EMH is mainly about if the historical prices of equities consisting of periods longer than a couple of days are informative or not.

We test the closing prices for three periods: From to 2015-04-15 to 2016-04-15, from 2014-04-15 to 2016-04-15, and from 2014-04-15 to 2015-04-15. The second and third tests´ major reason for existing can be found with Malkiel (2011), who argues that patterns yielded from technical analysis are merely coincidental, and that were the analysis to change its scope or focus, the pattern would disappear or get muddled. For this reason, it is necessary to test for a time period of different size in order see whether the lagged variables achieve statistical significance in that time period. Should the same variables not be significant, it would be a point in favor for the EMH.

### 3.3 Data Description

The data for our AR test has been gathered on the 16th May, 2016, from the online financial website Investing, and it was gathered on the following variables: Closing price, opening price, high price, low price, and volume traded in SEK. Investing was chosen as a source due to us finding the data easily available for the public to use, the variables in question being cleanly and consistently dated and summarized. The reason for the variables gathered is that this is the easiest data to gather information about, meaning it is widely available to the public, this is also data widely discussed in economic media.

The first time interval analyzed begins at 2015-04-15 and ends at 2016-04-15. In order to account for the lagged values that came before the interval start, with data stretching back to 2014-06-27 (200 days before 2015-04-15) is added. The second interval begins at 2014-04-15 and ends at 2016-04-15, and another 200 days added to the interval´s start. The third period starts at 2014-06-27 and ends at 2015-04-15, also with 200 days added before the start to account for the lagged data. The extra 200 days have been added to ensure that the entire intervals are observed in the tests.

### 3.4 Argument for Exogeneity

Since the AR model is based on asymptotic OLS, we argue that the closing price is contemporaneously exogenous from the other variables that are unobserved in the regression test. First, some general conditions need to be outlined:

$$x_t = (x_{t1}, x_{t2}, x_{t3}, \ldots, x_{tk}), \qquad [3.4]$$

($x_t$) in (3.4) is a shorthand for all explanatory variables which, when taking the other half of the equation into account, is considered to be representing the explanatory variables for all observed values of *t* (Wooldridge, 2013).

$$E(u_t|x_t) = 0 \qquad [3.5]$$

In (3.5) ($u_t$) represents the unobserved variables at time *t*, while ($x_t$) again stands as a shorthand for the independent variables at time *t*. The equation (3.5) states that $u_t$ and the explanatory variables $x_t$ are contemporaneously uncorrelated (Wooldridge, 2013).

In our study, the unobserved variables are the opening prices, the high prices, the low prices, and the volume. The explanatory variables are the lagged values on the closing price. The relation between the lagged closing prices and the other prices cannot be observed within a single time frame - they are effectively random in relation to each other (as seen on the candle charts of OMX Stockholm 30 at any given time period).

The volume variable in our data represents the velocity of cash-flow of a given time frame. We argue that volume as a single variable does not affect the lagged variables of closing prices. We concede that volume can affect the closing price, but that it cannot affect the lagged variables.

We aim to test if there is any information in lagged closing prices that has significant effect on closing prices at time t by using autoregression. The regression will show the statistical significance of predictability on closing price at time t by studying the coefficient of the lag.

### 3.5 Restrictions of the Study

Our study is performed over two years, namely 2014-2015. This is a relatively short period, limiting the number of our observations. However, the strength of the selected time period is that it contains up-to-date information, thus using the current conditions of trading and investment regarding the years chosen. This allows the study to examine if EMH holds on OMX Stockholm 30 index during the current market frictions.

There are also some ramifications of exclusively using the autoregressive model in the study to be noted. The use of the model allows us to examine the price history and the potential information contained within. The lack of using other econometric models means that testing the historical prices is the sole focus of this study, allowing us to examine them in greater detail.

## 4. Results and Discussion

### 4.1 Descriptive Statistics

Below are the tables for each of the three testing periods, detailing the variables present in the dataset, the number of observations, as well as the variables´ respective mean, standard deviation, and minimum and maximum values.

Table 4.1 Testing period 2015-2016

| Variable | Observations | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| | | | | | |
| Closing Price | 453 | 1480.852 | 115.8901 | 1247.06 | 1719.93 |
| Opening Price | 453 | 1481.803 | 115.713 | 1248.28 | 1713.79 |
| High Price | 453 | 1491.083 | 114.8821 | 1285.33 | 1720.02 |
| Low Price | 453 | 1470.353 | 116.0476 | 1246.56 | 1699.48 |
| Volume | 453 | 9.11e+07 | 2.79e+07 | 2.83e+07 | 2.23e+08 |
| 1-day Lag | 452 | 1481.072 | 115.9236 | 1247.06 | 1719.93 |
| 2-day Lag | 451 | 1481.287 | 115.9621 | 1247.06 | 1719.93 |
| 3-day Lag | 450 | 1481.484 | 116.0155 | 1247.06 | 1719.93 |
| 4-day Lag | 449 | 1481.74 | 116.0178 | 1247.06 | 1719.93 |
| 5-day Lag | 448 | 1481.993 | 116.0239 | 1247.06 | 1719.93 |
| 10-day Lag | 443 | 1483.504 | 115.7866 | 1247.06 | 1719.93 |
| 50-day Lag | 403 | 1495.596 | 113.8185 | 1269.91 | 1719.93 |
| 100-day Lag | 353 | 1507.235 | 113.7641 | 1269.91 | 1719.93 |
| 200-day Lag | 253 | 1503.46 | 127.2178 | 1269.91 | 1719.93 |

Table 4.1, summarized statistics of the time interval 2015-2016. Explanation of table 4.1; observations show the number of days observed. Mean, standard deviation, and minimum and maximum values are in index prices, except volume which is the trading volume in SEK per observed day.

Table 4.2 Testing period 2014-2016

| Variable | Observations | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| | | | | | |
| Closing Price | 700 | 1419.055 | 129.9201 | 1154.54 | 1719.93 |
| Open Price | 700 | 1419.581 | 130.2127 | 1154.66 | 1713.79 |
| High Price | 700 | 1427.426 | 130.9662 | 1154.73 | 1720.02 |
| Low Price | 700 | 1410.113 | 128.707 | 1141.9 | 1699.48 |
| Volume | 700 | 8.85e+07 | 2.61e+07 | 2.83e+07 | 2.23e+08 |
| 1-day Lag | 699 | 1419.109 | 130.0052 | 1154.54 | 1719.93 |
| 2-day Lag | 698 | 1419.159 | 130.0917 | 1154.54 | 1719.93 |
| 3-day Lag | 697 | 1419.197 | 130.1812 | 1154.54 | 1719.93 |
| 4-day Lag | 696 | 1419.273 | 130.2596 | 1154.54 | 1719.93 |
| 5-day Lag | 695 | 1419.346 | 130.3392 | 1154.54 | 1719.93 |
| 10-day Lag | 690 | 1419.862 | 130.6639 | 1154.54 | 1719.93 |
| 50-day Lag | 650 | 1423.443 | 133.4286 | 1154.54 | 1719.93 |
| 100-day Lag | 600 | 1424.278 | 137.2409 | 1154.54 | 1719.93 |
| 200-day Lag | 500 | 1405.776 | 140.0742 | 1154.54 | 1719.93 |

Table 4.2 summarizes the statistics of the time interval 2014-2016. Explanation of the table 4.2; observations show the number of days observed. Mean, standard deviation, and minimum and maximum values are in index prices, except volume which is the trading volume in SEK per observed day.

Table 4.3 Testing period 2014-2015

| Variable | Observations | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| | | | | | |
| Closing Price | 448 | 1380.204 | 124.1462 | 1154.54 | 1710.87 |
| Opening Price | 448 | 1379.736 | 123.3482 | 1154.66 | 1708.1 |
| High Price | 448 | 1385.983 | 124.4492 | 1154.73 | 1719.44 |
| Low Price | 448 | 1372.801 | 122.7519 | 1141.9 | 1699.48 |
| Volume | 448 | 8.43e+07 | 2.43e+07 | 2.83e+07 | 2.16e+08 |
| 1-day Lag | 447 | 1379.465 | 123.2945 | 1154.54 | 1710.87 |
| 2-day Lag | 446 | 1378.743 | 122.4838 | 1154.54 | 1710.87 |
| 3-day Lag | 445 | 1378.021 | 121.6658 | 1154.54 | 1710.87 |
| 4-day Lag | 444 | 1377.296 | 120.8367 | 1154.54 | 1710.87 |
| 5-day Lag | 443 | 1376.576 | 120.0179 | 1154.54 | 1710.87 |
| 10-day Lag | 438 | 1373.12 | 116.2177 | 1154.54 | 1710.87 |
| 50-day Lag | 398 | 1344.467 | 75.64921 | 1154.54 | 1575.95 |
| 100-day Lag | 348 | 1326.66 | 61.2706 | 1154.54 | 1424.93 |
| 200-day Lag | 248 | 1306.015 | 57.99217 | 1154.54 | 1406.44 |

Table 4.3 summarizes the dataset for the third test, time interval is 2014-2015. Explanation of the table 4.3; observation show the number of days observed. Mean, standard deviation, and minimum and maximum values are in index prices, except volume which is the trading volume in SEK per observed day.

## 4.2 The Initial Test´s Results for the time interval of 2015 to 2016

Table 4.4 Test results for the period 2015-2016

| Independent variables | Effect on closing price |
|---|---|
| 1-day lag | 0.873*** |
| | (0.070) |
| 2-day lag | -0.025 |
| | (0.095) |
| 3-day lag | 0.205** |
| | (0.096) |
| 4-day lag | -0.183** |
| | (0.084) |
| 5-day lag | 0.050 |
| | (0.062) |
| 10-day lag | 0.009 |
| | (0.031) |
| 50-day lag | -0.007 |
| | (0.021) |
| 100-day lag | -0.021 |
| | (0.014) |
| 200-day lag | -0.060*** |
| | (0.021) |
| Constant | 237.180*** |
| | (74.598) |
| Observations | 253 |
| R-squared | 0.966 |
| Robust standard errors in parentheses | |
| *** p<0.01, ** p<0.05, * p<0.1 | |

Table 4.4 displays the results of the AR(9) in the time period 2015-04-15 to 2016-04-15

Table 4.4 shows that the closing prices that were lagged by 1, 3, 4, and 200 days are statistically significant. This is in conclusion with Fama´s (1997) earlier studies regarding that there is price historic information in lags existing in shorter time periods, with the exception of the 200-day lag. Of those four, the variable with a 1-day lag had the greatest economic significance with a coefficient of 0.873. The 4-days and 200-days lagged variable have negative coefficients, meaning that a change in $y_{t-4}$ and $y_{t-200}$ will induce a change in the opposite direction on the closing price for any given value of t-j a positive change will have a negative effect, and vice versa. It must be noted, however, that these effects can be countered and overridden by the positive statistically significant variables, in particular by the 1-day lag which has the highest coefficient and therefore the greatest economic significance.

The coefficient on the 1-day lag indicates that there is a continuous trend of the previous closing price. Whilst the 4-day lag seems to indicate a mild trend reversal due its negative coefficient, the economic impact of it is relatively small in comparison to the 1-day lag.

The important thing to keep in mind in our test is that we are testing the strongest form of EMH. This is a theoretical model existing only in theory. The probability of a fully efficient financial market existing in the real world lies more in the realm of fiction rather than fact due to the divergent interests of the participants of the market. It is thus more reasonable to assume that everyone participating in the financial market can hardly know everything worth knowing about their equities, thereby the equities cannot reflect all the price information.

The results show that there is information contained in historical prices that do affect future prices on the OMX Stockholm 30. Thereby the strongest form of EMH can be rejected on the OMX Stockholm 30 as expected. Due to the volume trading in the OMX Stockholm 30 (143,487 mil. SEK, 2016-02-12) there is a sign that the participant do not fully believe in the strongest form of EMH. If the value of the equities were fully reflected in the price the trading volume of OMX Stockholm 30 would probably decline considerably depending on that arbitrage opportunities would not exist. This is of course assuming that the participants of the OMX Stockholm 30 equities are operating under a profit motive (a relatively safe assumption).

What is even more interesting, however, is that the 200-day lag is statistically significant. Though its effect is relatively minor in comparison to the other 3 significant variables, the possibility of a price so far back in time playing a role in the present OMX Stockholm 30 price is noteworthy. However, the other two long-term lags (the 50-day and 100-lags) do not achieve significance, raising the issue of why only the 200-day lag shows significance. The burning question thus becomes the following: Is this just an anomaly, an odd coincidence where the numbers aligned up well?

The other two studies in the time periods 2014-04-15 to 2016-04-15 and 2014-06-27 to 2015-04-15 do not provide a clear answer to this.

### 4.3 The Follow-up Tests, tests for time periods 2014-04-15 to 2016-04-15 and 2014-06-27 to 2015-04-15

The second test concerns the two-year period 2014-04-15 to 2016-04-15, whose variable data described in table 4.5:

Table 4.5 Test results for the period 2014-2016

| Independent variables | Impact on closing price |
|---|---|
| 1-day lag | 0.889*** |
| | (0.053) |
| 2-day lag | 0.069 |
| | (0.072) |
| 3-day lag | 0.163** |
| | (0.076) |
| 4-day lag | -0.159** |
| | (0.066) |
| 5-day lag | 0.012 |
| | (0.051) |
| 10-day lag | 0.013 |
| | (0.024) |
| 50-day lag | 0.008 |
| | (0.013) |
| 100-day lag | -0.013 |
| | (0.012) |
| 200-day lag | -0.002 |
| | (0.008) |
| Constant | 28.982** |
| | (11.901) |
| Observations | 500 |
| R-squared | 0.977 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.5 displays the results of AR(9) in the time period 2014-04-15 to 2016-04-15

The second test (2014-16) has yielded similar short term results, as can be seen in table 4.4: The lags on the first, third, and fourth are all statistically significant. The 200-day lag has become insignificant, however, resulting in the insignificance of all the long-term lags. It could also be taken as indicative of the idea that the significance of 200-day lag in the previous test may just have been an anomaly. The question of why the second lag is insignificant remains unanswered though. This aligns fairly neatly with Fama´s (1997) supposition that current and recent prices will impact the pricing in the near future.

Finally, the third test (2014-15) (outlined in table 4.5) shows a different short-term result (displayed in table 4.6) from the other two tests, namely that while the 1-day lag is still significant, the 3-day and 4-day lag no longer are. Furthermore, the lag on the second day has now become statistically significant. In the long term, the 200-day lag is now significant and positive, which is in line with the first test, lending credence to the idea that the 200-day lag may actually have some (if minor) predictive power of the closing prices in the present.

Table 4.6 Test results for the period 2014-2015

| Independent variables | Impact on closing price |
|---|---|
| 1-day lag | 0.795*** |
| | (0.068) |
| 2-day lag | 0.279*** |
| | (0.085) |
| 3-day lag | 0.078 |
| | (0.089) |
| 4-day lag | -0.126 |
| | (0.084) |
| 5-day lag | -0.077 |
| | (0.082) |
| 10-day lag | 0.024 |
| | (0.035) |
| 50-day lag | 0.027 |
| | (0.027) |
| 100-day lag | -0.024 |
| | (0.028) |
| 200-day | 0.057** |
| | (0.029) |
| Constant | -39.653 |
| | (30.768) |
| Observations | 248 |
| R-squared | 0.989 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.6 displays the results of AR(9) in the time period 2014-06-27 to 2015-04-15

When viewed together, these results become rather difficult to interpret. The 200-day lag, for instance, is significant in the tests on a single year, but with different implications in each of them. In the first test the lag is negative, indicating a trend reversal, while in the second it is positive, indicating a continuation of a trend. But the lag is not significant in the test for two years. On one hand the collective results seem to indicate that the 200-day lag can potentially be slightly useful when predicting the OMX Stockholm 30 on a single year basis. On the other hand, its insignificance in the two-year test could potentially be taken to mean that by viewing the years in aggregate, in the big picture, the 200-day lag could be interpreted to not really being a useful indicator.

The latter option is reinforced by the small coefficient of the 200-day lag in both single year studies, indicating small economic significance. This would imply that even if the numbers align up just right the actual effect remains still within the realm of negligibility.

### 4.4 Notes on the R-squared

The R-squared of the three regressions are all very high, with the value coming very close to equaling 1. This not entirely strange, what with this study being about time series analysis of lagged dependent variables. However, we should be careful not to assume that the closing price is explained to such a great extent by past closing prices. Time series data in general tends be aggregate in nature and it can argued with relative ease that it is so in this case, seeing as the OMX Stockholm 30 is calculated from a set of equities (Nasdaq, 2014).

### 4.5 Discussion of Statistical and Economic Significance of our regression

Since there are statistically significant variables in our test, the null hypothesis is rejected, thereby implying the strongest form of EMH namely, that all available information is contained in the price, does not hold true on the OMX Stockholm 30 index.

The economic significance in our autoregression is implemented per unit, thereby stating that one unit change multiplies with the coefficient. For example if the change on closing price is 14 points on the OMX Stockholm index at time $t$, the result interpreted on the 1-day lag would be that 14 multiplied with 0.873.

By this implying that a large change between opening price and closing price would upgrade the significance of the variable, but it will be less significant by the time $t$-4 than it was in $t$-1. Thereby a large change between opening prices in one variable that has traveled from $t$-1 to $t$-4, can still have a more significant impact on time t than a smaller change has in $t$-1 at the same time interval studied. Thereby the $t$-4 day lag can override the $t$-1 day lag regarding price direction at time $t$ even when the 1-day lag is more economic significant.

We find important information contained in the economic significance of our statistically significant values. The economic significance is diminishing the further back the statistically significant lag goes. We are interpreting it as information gets contained in the lags over time. As for example when information has reached the 4-day lag its economic significance has become lesser, implying the information has already been largely utilized.

Following this hypothetical scenario to its conclusion, this would indicate that, assuming no shocks of any kind, when $t \to \infty$ the closing price would eventually stabilize at its true value and the information about the equity will be contained in the price. This can be further interpreted to mean that while the strong form of EMH does not apply to the OMX Stockholm 30 index, one of the two other forms - the weak and the semi-strong form - might do so.

The economic and statistical significance on the 1-day lag is large throughout all three tests. Thus it being economic and statistic significant it does not necessarily imply that the trend will be continuous from the one day lag. A highly bearish closing day can imply that the following day will be bullish depending on how it is interpreted. As for example, after a highly bearish day at time $t$-1 some may think the equities are cheap and push the buy button putting up pressure on buying prices, thereby making the closing day at time t go bullish. On the other hand a highly bearish day at time $t$-1 can be interpreted as the market is weak making people sell putting further down pressure on selling prices. This can be interpreted to mean that, even though roughly about 80 percent of the price change in time $t$-1 can be applied on time $t$, it does not necessarily imply a continuous trend.

### 4.6 Our Results in Relation to the Theories

Because of the presence of statistically significant lagged variables obtained in our AR-tests, we can assume that there is information to be gleaned from historical prices on the OMX Stockholm 30 index, thereby making us able to rule out the presence of the strongest form of EMH on it. On the other hand, the weak and semi-strong forms of EMH cannot be rejected on such basis, as both allow for the presence of lagged information (Fama, 1970).

In our test we have noticed that the 200-day lag have shown statistical significance in two of the analyzed time periods, namely 2014-2015 and 2015-2016. Therefore the 200-day lag can be said to be statistically significant. At the same time, however, it also has a fairly weak economic significance in both of those tests, meaning that it has a rather weak impact on the current closing price.

This result on the 200-day lag can vaguely be interpreted in relation to the Dow Theory by Charles Dow (1890) that markets move in bear or bull trends, and that trending of the markets is a possibility. We do however have limitations in our test to fully conclude longer trend movements due to the limitation of longer trend tests thus us only using three different lags (50, 100 and 200 day lags).

In conclusion with our results regarding behavioural finance and chart pattern recognition, we can with the awareness of our tests limitations carefully state that if chart pattern recognition should be used, the best use for them probably would be in a short window time frame. Leaning on our findings that the shorter lags have more economical significance than the longer ones.

In all of the three tests 2015-2016, 2014-2016 and 2014-2016 the result obtained is that there is statistical and economical significance foremost on the short lags. These results are in line with Fama´s (1997) earlier studies regarding that there is price historic information in lags existing in shorter time periods.

With regards to the Random Walk model, the statistically significant coefficients in the short-term period imply that since there is some form of pattern in the price movement, the Random Walk will not apply on that period. In mathematical terms this can be written as:

$$f\,(p_{j,\ t+1} \mid \Phi_t\,) \neq f\,(p_{j,\ t+1}) \qquad [4.1]$$

The model (4.1) states that the future price (p) of the security (j) is not independent of the information contained in $\Phi_t$.

In the long-term period, however, it gets a bit muddled. The statistical significance of the 200-day in the two tests with one-year periods could be seen as a point against the Random Walk model, but on the other hand, the economic significance is fairly small. This makes it difficult to reject the model on that basis alone, since the effect could be interpreted to negligible.

## 5. Conclusion

The assumption that any lag of a price change is short lived seems to apply at the OMX Stockholm 30 between 2014 and 2016. We find that the 1-day lag is consistently statistically significant throughout all of the three regressions. The 5-day, 10-day, 50-day, and 100-day lag are always insignificant, while the remaining ones are inconsistent.

The coefficient on the 200-day lag have different interpretations depending on the testing period, whilst it is negative in the period 2015-04-15 to 2016-04-15 indicating a minor trend reversal, the same lagged value is positive in the time period 2014-06-27 to 2015-04-15 indicating a continuous trend. The value of coefficients are relatively small; -0.06 and 0.057, respectively . This can potentially be interpreted as "noise", as Fisher Black (1986) would call it, due to its low economic significance.

What is relatively clear, however, is that the results allow us to reject the strongest form of EMH on the OMX Stockholm 30, since we have found statistical significance in historical prices (lagged values) in our test, implying that information can be gleaned from them. We do not, however, reject the entire EMH theory since the two weaker forms of the EMH allow for the existence of lagged information, while there is no such permissiveness in the strongest form of EMH.

Due to that the autoregressive model´s results show that there is information in the historical prices affecting future prices we can carefully state that there may be some kind of predictability of future prices in a short window in the OMX Stockholm 30. This is fairly in line with what Fama (1997) has stated, that any lag in the response of prices to an event is short lived:

"The assumption in studies that focus on short return windows is that any lag in the response of prices to an event is short-lived."

- Fama, E., 1997, p. 284

Our results show that there is value in including the weak form and the semi-strong form of EMH in the trading strategy. This can be seen in the diminishing economic significance of the significant variables in all of our three tests the further back the lags are in time. The diminishing economic significance is interpreted to mean that the information gets contained in the price over time.

## 6. References


Black, Fisher. 1986. *Noise.* The Journal of Finance, 41, 529-544.

Brock, William. Lakonishok, Josef. LeBaron, Blake. 1992. *Simple Trading Rules and the Stochastic Properties of Stock Returns.* Journal of Finance, Volume 47, Issue 5.

Brown, Stephen J. Goetzmann, William N. Kumar, Alok. 1998. *The Dow Theory: William Peter Hamilton's Track Record Reconsidered.* The Journal of Finance Vol LIII, No. 4 1311-1332.

Fama, Eugene F. 1970. *Efficient Capital Markets: A Review of Theory and Empirical Work*. Journal of Finance, Vol.25, Issue.2, pp. 383-417.

Fama, Eugene F. 1997. *Market efficiency, long term returns, and behavioral finance.* Journal of Financial Economics 49, p283-306.

Grossman, Sanford J. Stiglitz, Joseph E. 1980. *On the Impossibility of Informationally Efficient Markets.* American economic review, 70, 393-408.

Hamilton, William Peter. Rhea, Robert. 2015. The Dow Theory. Horizon Publishing Company.

LeRoy, Stephen F. 1973. *Risk Aversion and the Martingale Property of Stock Prices,* International Economic Review, Vol.14, No.2.

Lo, Andrew W. MacKinlay A. Craig. 1999. A Non Random Walk Down Wall Street. Princeton University Press.

Lo, Andrew W. Mamaysky, Harry. Wang, Jiang. 2000. *Foundations of Technical Analysis: Computational Algorithms, Statistical Inference, and Empirical Implementation.* The Journal of Finance, Vol.LV, NO.14.

Lucas, Jr. Robert E. 1978. *Asset Prices in an Exchange Economy.* Econometrica, Vol. 46, No 6, p 1429-1445.

Malkiel, Burton G. 2003. *The Efficient Market Hypothesis and Its Critics*. CEPS Working Paper No. 91.

Malkiel, Burton G. 2011. A Random Walk Down Wall Street. W. W. Norton & Company.

Nasdaq. 2014. Rules for the construction and maintenance of the OMX STOCKHOLM 30 INDEX, version 1.5. Retrieved 2016-05-19 from https://indexes.nasdaqomx.com/docs/Methodology_OMXS30.pdf

Wooldridge, Jeffrey M. 2013. Introduction to Econometrics, Europe, Middle East & Africa Edition. Cengage Learning EMEA.

# 7. Appendix

Table 4.1 Testing period 2015-2016

| Variable | Observations | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| | | | | | |
| Closing Price | 453 | 1480.852 | 115.8901 | 1247.06 | 1719.93 |
| Opening Price | 453 | 1481.803 | 115.713 | 1248.28 | 1713.79 |
| High Price | 453 | 1491.083 | 114.8821 | 1285.33 | 1720.02 |
| Low Price | 453 | 1470.353 | 116.0476 | 1246.56 | 1699.48 |
| Volume | 453 | 9.11e+07 | 2.79e+07 | 2.83e+07 | 2.23e+08 |
| 1-day Lag | 452 | 1481.072 | 115.9236 | 1247.06 | 1719.93 |
| 2-day Lag | 451 | 1481.287 | 115.9621 | 1247.06 | 1719.93 |
| 3-day Lag | 450 | 1481.484 | 116.0155 | 1247.06 | 1719.93 |
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| 10-day Lag | 443 | 1483.504 | 115.7866 | 1247.06 | 1719.93 |
| 50-day Lag | 403 | 1495.596 | 113.8185 | 1269.91 | 1719.93 |
| 100-day Lag | 353 | 1507.235 | 113.7641 | 1269.91 | 1719.93 |
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Table 4.2 Testing period 2014-2016

| Variable | Observations | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| | | | | | |
| Closing Price | 700 | 1419.055 | 129.9201 | 1154.54 | 1719.93 |
| Open Price | 700 | 1419.581 | 130.2127 | 1154.66 | 1713.79 |
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| 5-day Lag | 695 | 1419.346 | 130.3392 | 1154.54 | 1719.93 |
| 10-day Lag | 690 | 1419.862 | 130.6639 | 1154.54 | 1719.93 |
| 50-day Lag | 650 | 1423.443 | 133.4286 | 1154.54 | 1719.93 |
| 100-day Lag | 600 | 1424.278 | 137.2409 | 1154.54 | 1719.93 |
| 200-day Lag | 500 | 1405.776 | 140.0742 | 1154.54 | 1719.93 |

Table 4.2 summarizes the statistics of the time interval 2014-2016. Explanation of the table 4.2; observations show the number of days observed. Mean, standard deviation, and minimum and maximum values are in index prices, except volume which is the trading volume in SEK per observed day.

Table 4.3 Testing period 2014-2015

| Variable | Observations | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| | | | | | |
| Closing Price | 448 | 1380.204 | 124.1462 | 1154.54 | 1710.87 |
| Opening Price | 448 | 1379.736 | 123.3482 | 1154.66 | 1708.1 |
| High Price | 448 | 1385.983 | 124.4492 | 1154.73 | 1719.44 |
| Low Price | 448 | 1372.801 | 122.7519 | 1141.9 | 1699.48 |
| Volume | 448 | 8.43e+07 | 2.43e+07 | 2.83e+07 | 2.16e+08 |
| 1-day Lag | 447 | 1379.465 | 123.2945 | 1154.54 | 1710.87 |
| 2-day Lag | 446 | 1378.743 | 122.4838 | 1154.54 | 1710.87 |
| 3-day Lag | 445 | 1378.021 | 121.6658 | 1154.54 | 1710.87 |
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| 10-day Lag | 438 | 1373.12 | 116.2177 | 1154.54 | 1710.87 |
| 50-day Lag | 398 | 1344.467 | 75.64921 | 1154.54 | 1575.95 |
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| 200-day Lag | 248 | 1306.015 | 57.99217 | 1154.54 | 1406.44 |

Table 4.3 summarizes the dataset for the third test, time interval is 2014-2015. Explanation of the table 4.3; observation show the number of days observed. Mean, standard deviation, and minimum and maximum values are in index prices, except volume which is the trading volume in SEK per observed day.

Table 4.4 Test results for the period 2015-2016

| Independent variables | Effect on closing price |
|---|---|
| 1-day lag | 0.873*** |
| | (0.070) |
| 2-day lag | -0.025 |
| | (0.095) |
| 3-day lag | 0.205** |
| | (0.096) |
| 4-day lag | -0.183** |
| | (0.084) |
| 5-day lag | 0.050 |
| | (0.062) |
| 10-day lag | 0.009 |
| | (0.031) |
| 50-day lag | -0.007 |
| | (0.021) |
| 100-day lag | -0.021 |
| | (0.014) |
| 200-day lag | -0.060*** |
| | (0.021) |
| Constant | 237.180*** |
| | (74.598) |
| Observations | 253 |
| R-squared | 0.966 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.4 displays the results of the AR(9) in the time period 2015-04-15 to 2016-04-15

Table 4.5 Test results for the period 2014-2016

| Independent variables | Impact on closing price |
|---|---|
| 1-day lag | 0.889*** |
| | (0.053) |
| 2-day lag | 0.069 |
| | (0.072) |
| 3-day lag | 0.163** |
| | (0.076) |
| 4-day lag | -0.159** |
| | (0.066) |
| 5-day lag | 0.012 |
| | (0.051) |
| 10-day lag | 0.013 |
| | (0.024) |
| 50-day lag | 0.008 |
| | (0.013) |
| 100-day lag | -0.013 |
| | (0.012) |
| 200-day lag | -0.002 |
| | (0.008) |
| Constant | 28.982** |
| | (11.901) |
| Observations | 500 |
| R-squared | 0.977 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.5 displays the results of AR(9) in the time period 2014-04-15 to 2016-04-15

Table 4.6 Test results for the period 2014-2015

| Independent variables | Impact on closing price |
|---|---|
| 1-day lag | 0.795*** |
| | (0.068) |
| 2-day lag | 0.279*** |
| | (0.085) |
| 3-day lag | 0.078 |
| | (0.089) |
| 4-day lag | -0.126 |
| | (0.084) |
| 5-day lag | -0.077 |
| | (0.082) |
| 10-day lag | 0.024 |
| | (0.035) |
| 50-day lag | 0.027 |
| | (0.027) |
| 100-day lag | -0.024 |
| | (0.028) |
| 200-day | 0.057** |
| | (0.029) |
| Constant | -39.653 |
| | (30.768) |
| Observations | 248 |
| R-squared | 0.989 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.6 displays the results of AR(9) in the time period 2014-06-27 to 2015-04-15