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Using Commodities to Predict the Swedish Stock Market

NEKN01 – Master essay in Economics

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Abstract

This thesis will try to answer the question if it is possible to use commodities to predict the Swedish stock market. The question is answered by searching for an in-sample and out-of-sample predictability relationship between commodity returns and stock returns. Different commodity indices are used in the thesis as predictors in order to predict the general Swedish OMX Stockholm 30 stock index but also to predict eight chosen Scandinavian stocks active in different sectors of the market. This thesis is the first academic paper to do so using an econometrical approach.

The thesis starts with an introduction to the stock and commodity market. The link between both markets is discussed and using previous research it is shown that it should be possible to predict stock returns using commodities, at least to some extent. Then follows a theory part where prediction of returns is discussed using the Efficient Market Hypothesis. The hypothesis states that using historical data to predict future returns should be impossible because the market is effective. To test the hypothesis an empirical analysis in several steps follows where it is proved that the hypothesis does not hold since the predictability link between some of the commodity indices used as predictors and the predicted stock returns is strong and robust. The highest level of predictability with a possibility to explain 14.67 % of the one period ahead return in-sample and 13.98 % of the return out-of-sample is achieved using the London Metal Exchange index as a predictor on the Swedish mining company Boliden.

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1. Introduction

This thesis will search for an in-sample and out-of-sample predictability relationship between commodity returns and stock returns. Different commodity indices are used as predictors in order to predict the general Swedish OMX Stockholm 30 stock index and to predict eight chosen Scandinavian stocks active in different sectors of the market. Since the stock market accumulates large amounts of money, for example in 2012 the value was 561 Billion USD for Sweden and 18,668 Billion USD for the US (Quandl, 2015), a possibility to predict future stock returns would give investors large opportunities to make money or reduce losses.

The interest in prediction of investments is nothing new. In 1925 the American researcher Sarle tried to predict the future price of certain commodities related to farming by looking at historical data (Sarle, 1925). The idea of predicting stock returns became more prolific as the stock markets grew bigger and accumulated more money, and in the 1960s several papers were released on the subject of predictability of stock returns. While some researchers claimed that returns were possible to predict using fundamental analysis or "charting" (what we today call technical analysis), other researchers claimed that there actually does not exist a general predictability in stock returns since the stock markets are efficient already. Those theorists instead supported the idea that market returns come from the existence of random walks where the future return has nothing to do with the previous return. The new availability of computers that could help process econometrical and financial data helped advancing the research and the models used, but still did not help researchers come to a general conclusion if stock markets actually are efficient or not (Fama, 1965).

Still today, the existence of efficiency is a heavily debated and researched topic in the financial and academic world. The idea that stock returns follow a random walk eventually led to the creation in 1965 of what is still a frequently used and discussed theory, the so called "Efficient Market Hypothesis". The hypothesis has since been developed further and one of its inventors, Eugene Fama received a Nobel Memorial Prize in Economics 2013 for his work in the subject. The work of Fama based on the hypothesis is said to have influenced the creation of the index funds (The Nobel Museum, 2013). The hypothesis states that predictability using already available data should be impossible since the stock market is already efficient. If it actually is possible to predict stock returns, then the hypothesis cannot hold and the market is not rational (Lo, 2007). The hypothesis has been scrutinised and while some researchers and analysts believe in market efficiency, others do not agree that markets actually are efficient. There will be more information in Chapter 2 – Theory about the hypothesis and the arguments that the believers and the non-believers of the hypothesis use.

On the subject of using commodities to predict stock returns, previous research has been done although to a small extent, and only a few papers exist today in the topic (Black et al, 2014). The few examples of papers are Bakshi et al (2011) that use the Baltic Dry shipping index as a predictor of stock returns. Jacobson et al (2013) use industrial metals as predictors of stock returns, Creti et al (2012) test different commodity indices against stock returns and Black et al (2014) use several commodities to predict the US stock market. All mentioned papers use different methods and models to test for a predictability relationship. This thesis will contribute by being the first where commodities are being used specifically to predict the Swedish stock market and to predict individual stocks instead of general stock indices.

In the fall of 2015, the Standard & Poor GSCI Commodity Index and the Bloomberg Commodity Index, which are two of the biggest commodity indices in the world (Bloomberg, 2015; SP Indices, 2015) both hit their lowest point since the start of the new millennium after dropping over 30 % since the summer of 2014. The steep fall is said to have come mainly from decreasing economic growth in China and lower than expected inflation in both the European and American economies (Collins, 2015). At the same time, major stock market indices like the SP 500 Composite Index for the US and the OMXS30 Index for Sweden were not affected. Between 2008 and 2013 the correlation between stocks and commodities were high however (Dicolo, 2013).

Commodities play an important role in the world economy because production of goods needs commodities as an input. The world commodity market is hard to value because a lot of the trading is done in so many scales and sometimes outside of regulated markets like an exchange. Another problem is what exactly to classify as a commodity. Though it is expected that the total value of the petroleum products including oil, gold, copper, aluminum, soy bean and coal trade combined in 2014 were worth 3.6 trillion USD (International Trade Center, 2015). Since commodities are used as inputs for production, the trade in them plays a key role in analysing business cycles and trade flows. Garner (1989) showed in his research that commodity trade can also be used to predict Consumer Price Index (CPI) inflation.

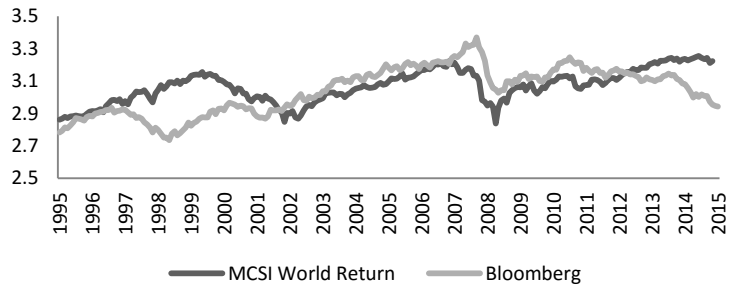
The commodity market is driven mostly by shocks in supply and demand (Creti et al, 2012). An example is the oil crises in the 1970s, where negative supply shocks created by the oil producing cartel OPEC caused large price increases in oil, which stands for the biggest part of the commodity trading (International Trade Center, 2015). Though in later years, commodities or derivatives of commodities have been increasingly used in portfolios as a pure speculative investment, especially when stock markets have had low returns. This has added risk premium as another driving force behind commodity pricing (Creti et al, 2012). Stock prices on the other hand are driven by

expectations of future cash flows, most commonly in the form of dividends and expected returns in the form of the risk premium (Shiller, 1988).

The links between commodities and stocks are multiple but not always direct. Companies produce, refine and transport commodities. In the last step of the value chain, consumers buy the products produced from commodities. It can be everything from the bread loaf that we eat in the morning (produced using the commodity wheat), the petrol we put in our car (a commodity itself, but also produced from the commodity oil), the house we live in (built using the commodities timber and concrete) to the computer we write on (made with several commodities including polymer, copper and lithium and then powered by the commodity electricity). The more goods demanded by consumers and therefore sold by companies, the more commodities are needed. There should therefore by intuition be some kind of link between commodity return and the stock return. However, the relationship is not as direct as it first seems. In some cases an overflow of commodities on the market means that the commodity prices will go down or halt but companies that produce goods from commodities will make bigger profits since the inputs in their production now cost less. This is called a supply cushion and usually gives rise to positive stock returns. The falling oil and iron prices since 2013 is an example of this effect (Dicolo, 2013).

Another factor to consider is that rising commodity prices push up the price of goods leading to higher inflation, which in turn leads to higher interest rates that slow down the activity in the economy which is not good for stock returns (Black et al, 2014). In some periods since the 1960s, there has actually been a negative correlation between commodity returns and stock returns (Gorton and Rouwenhorst, 2006). However, lower prices of certain commodities like copper because of lower demand could also be an indicator that the market is slowing down with falling stock returns as an effect. Basak and Pavlova (2013) have also showed that when commodities are being “Financialized”, that means traded more as speculative assets in a portfolio context, the correlation between commodities and stocks has become stronger.

Diagram 1 – MCSI World Return and Bloomberg Commodity Index



Above in Diagram 1, the two logged indices MSCI World Return for global stock returns and Bloomberg Commodity Index for commodities are presented. The correlation between the indices is 0.49. Even though the relationship between commodity returns and stock returns sometimes is indirect as explained earlier, there still exists a link. Research by Black et al (2014) uses cointegration testing to show that there is a link between commodity returns and stock returns that can be used for predictability, though the link is not so strong. Gorton and Rouwenhorst (2006) argue that in the long run stocks and commodities should both increase in value since they both are dependent on future economic performance and the economy tends to increase over time. Creti et al (2012) and Basak and Pavlova (2013) both look into the link between commodities and stocks and find that the correlations have increased since the financial crisis.

So there seems to be a link between commodities and stocks and both commodities and stocks play an important role in the world economy, and since there has not been any research done on using commodities to predict the Swedish stock market, this thesis will fill that hole and try to answer the questions: Can commodities be used to predict the return of the Swedish stock market or does the Efficient Market Hypothesis hold and there is no predictability relationship? If there is a relationship, how big is it?

In the next chapter, the theory concerning The Efficient Market Hypothesis and stock predictions will be discussed.

2. Theory – Efficient Market Hypothesis

"The efficient markets hypothesis (EMH) maintains that market prices fully reflect all available information at all times". The theory was created by the two economists Eugene Fama and Paul Samuelsson independently of each other in the 1960s (Lo, 2007). The hypothesis states that all stocks on a liquid market are valued according to the information that is currently available to everyone participating in the market. When new information comes to the market, competition among traders and investors will make sure that the stock prices adapt directly and therefore are always valued at a fair price where supply and demand of the stock meet. In essence, the market is effective. It should be impossible to get a higher return by using fundamental analysis since all information is already in the price of the stock, and because the stock market follows a Martingale process where the mean of the past never can be used to predict or forecast the future mean of the return. It should not be possible to get a higher return than what the market as a whole offers with anything but pure luck, and prediction and forecasting should not work since the returns are just a random walk (Malkiel, 2003).

According to the hypothesis, an uninformed investor can buy a diversified portfolio, and since the market is effective, the investor will get a return equivalent to the return performed by professional investors like fund managers operating on the same market. Professional investors may get a higher initial return, but the transaction and research cost will clear out any arbitrage possibility over just buying the market portfolio (Clarke et al, 2001). Since active speculation is costly, the average active investor should get a lower return compared to just investing passively on the market.

Still today, even though EMH is one of the most studied hypotheses in all of the social sciences, there is no consensus among financial economists and behavioral economists as to whether the hypothesis actually holds or not. An analysis done by Sewell (2012) looked into other already published research papers discussing the EMH. The conclusion was that slightly under half of the papers supported the EMH. Depending on what article you read, the author will often come out strongly for or against the hypothesis.

The EMH is important for this thesis since predictability should not be possible if the hypothesis holds. Therefore, the result from the upcoming empirical analysis will either give proof to the hypothesis or reject it.

2.1. The three forms of efficiency

EMH states three forms of efficiency (Fama, 1965):

1. Weak efficiency where historical data cannot be used for predicting future returns.
2. Semi-strong efficiency which incorporates the requirements for weak efficiency but also includes all publicly available information in the prices of the stocks.
3. Strong efficiency. Incorporates the requirements for semi-strong efficiency but also all other information no matter if it is publically available or not. For example insider information is included in the prices.

2.2. Criticism of the hypothesis

Fama shared his Nobel Prize in 2013 with two other economists, Robert Shiller and Lars Peter Hansen (The Nobel Museum, 2013). Shiller who also has based much of his research on the EMH has come to the conclusion that stock markets are not efficient and he argues that the measures of volatility in the returns are far too great to be attributed to just new information. In essence, markets are not efficient since they do not implement new information correctly (Shiller, 1980). Investors tend to overreact to information and overbuy respectively oversell stocks when new information becomes available. The market will at some point correct this (sometimes called a “recoil”). Bondt and Thaler (1984) proved that by buying so called “loser stocks”, stocks that have had a negative return because

of bad news, it is possible to make a profit and outperform the market by 19.6 % over a three year period.

If the EMH is true, then there should not be any point in active stock placement since that will not give a higher return over the market and active placement usually involves higher transaction and administrative costs than passive investing like an index fund with no or low administrative fees. Still the market is full of active investments that investors choose to invest in. Coval et al (2005) have proved with their research that skillful and active investors can persistently get a higher return from their investments than the return offered on the market, this without trading in just small or illiquid companies. This conclusion shows that semi-strong efficiency cannot hold.

Different people put different values on stocks and other financial securities depending on their views on how to value risk, their interests, their risk premiums and several other factors. What one investor considers being a fully valued stock may be undervalued by another investor just because they have different views on how the company will perform in the future. One investor may value higher dividend yields over stock returns while another investor does not take dividends at all in consideration and only values long time stock returns.

Research of American insider transactions has proved that the average transaction made on illegal insider information gives an average return of 35 % over just 21 trading days of holding which is much higher than the average market return on investing without having any insider information. Besides the legal risk, the investments based on insider information are almost risk free (Ahern, 2014). This clearly rules out the existence of strong efficiency on stock markets.

Peter Lynch, manager of the Magellan Fund for Fidelity investments managed to get an average annual return of 29.2 % between 1977 and 1990 beating the general S&P 500 index by more than 100 %. Lynch claims he has the proof that by using predictions and fundamental analysis it is possible to outperform the market. Lynch believes strongly in using the local advantage of knowledge when investing (Clarke et al, 2011). An investor with a deep interest in forestry probably knows more about forestry companies and how to value them than the average investor. Therefore the investor with the deep special knowledge should use this skill to find undervalued stocks.

Other investors like Warren Buffet and George Soros have proved that they can beat the market over long periods of time by picking undervalued stocks.

2.3. Support of the hypothesis

Malkiel has by changing the definition slightly of what an efficient market is managed to prove that markets can be considered efficient. His definition of an effective market is: “Efficient markets do not allow investors to earn above-average returns without accepting above average risks” (Malkiel, 2003). Using Malkiels definition means that markets can be efficient even during bubbles like the dot-com bubble or the financial crisis in 2007-2008 (the case of bubbles is one of the argument used against the EMH), simply because investors accepted a risk that was over the average market risk in hope of a return that was over market average. It is worth noticing however that the efficiency Malkiel has proved holds, is still not the same definition of market efficiency as the one that constitutes the Efficient Market Hypothesis created by Fama and Samuelsson.

Another argument for the EMH is the chance of luck. With enough investors on the market there will be a few that get a return over the one offered on the market consistently just by pure luck. If there is a 50 % chance of beating the market over a year by pure luck, then over a ten year period there is a 63 % chance that at least one investor out of 1000 will beat the market consecutively every year by pure luck (Clarke at al, 2001). The higher the number of investors, the higher is the likelihood that some will be lucky and get a higher return than the return that the market offers. Earlier mentioned investors like Lynch, Buffet and Soros do not have to be any proof at all that the EMH does not hold since they can just be random lucky shots from a big distribution of investors. This goes hand in hand with research done by Lakonishok et al (1992) and Malkiel (1995) that showed that mutual funds do not beat the market over time and that an investor will make the most profit by just investing in a passive investment like an index fund. To prove their result further, funds were separated into groups with the worst performing funds and the best performing funds over a chosen period. The conclusion was that funds that had performed well one period did not perform well the next period on average.

In the next chapter, data will be analysed in order to see if it actually is possible to predict the Swedish stock market in general and certain stocks separately or if the Swedish stock market is effective to the extent that no link of predictability exists.

3. Empirical Analysis

In order to answer the question of the thesis, several steps of testing will be executed in order to determine what predictability certain commodities have on stocks.

3.1. Data used

All data used in the analysis are collected from Thomson Reuters Datastream. All data are in the form of time series data between October of 1995 and October of 2015. This thesis uses monthly data giving a total of 240 observations per time series (200 for Boliden since they have only been on the stock market since 2001). All data is logged to smoothen it in order to make it more suitable for econometrical modelling. The choice of what indices to use is based on previous research and the idea to use indices that have some kind of relationship to the Swedish economy.

The Swedish export of forestry products in 2011 totaled 16 Billion USD, making up for 10.5 % of the total Swedish export (Svensén, 2013). Therefore the Lumber Random Length Chicago Mercantile Exchange (hereafter Forest) is one of the commodity indices used. The index is made up from the daily lumber futures trade at the Chicago Mercantile Exchange which is the largest trading place in the world for derivatives related to forestry products (CME Group, 2015). A European or Swedish index over forestry products would have been more useful, but no such index with a suitable time length and with monthly observations exists.

The second index used is the London Metal Exchange Index (hereafter LME) which is an index made up of the trade in the six largest non-ferrous metals (aluminum, copper, zinc, lead, nickel and tin) at The London Metal Exchange. The exchange is the world's largest trading place for non-ferrous metals, steel billets and derivatives related to non-ferrous metals (London Metal Exchange, 2014). The use of this index is motivated by the successful predictions by Jacobson et al (2014) where they proved that metals are good predictors. Jacobson et al (2014) used other indices than LME however. The choice of using LME in this thesis related to the belief that the metals in LME suits the metals produced by public listed companies in Sweden better.

The third index used is the Baltic Dry Shipping Index (hereafter BDI). The index is a composite made up from weighted averages of daily quotes over time charter contracts for different sized ships carrying dry bulk goods (in other words dry commodities like iron ore, grains, coal, steel and timber) over different routes throughout the world. If the demand for commodities goes up, then the demand for transporting the commodities should intuitively go up as well. The contracts are traded at the Baltic Exchange in London, which is the world's largest trading place for freight contracts (Baltic Exchange, 2015). The BDI has previously been used to predict the general stock market returns in similar research by Bakshi et al (2011) and will therefore also be used in this thesis.

The Bloomberg Commodity Index (hereafter Bloomberg) and the Standard & Poor GSCI Commodity Index (hereafter SP) are more general commodity indexes adding more commodities, for example

energy and agricultural prices. SP puts a heavier weight on energy in the form of oil, natural gas and petroleum products than Bloomberg does. Since the prices of oil has decreased with 56 % from the start of 2014 to November 2015 (Datastream, 2015), the difference in the weighting of the two indices is worth noticing. SP has fallen more than Bloomberg since the beginning of 2014. The correlation between the two indices is still 0.9 however which has to be considered high.

The OMX Stockholm 30 Index (hereafter OMX) is the index used for the general Swedish stock returns. The Index is made up from the thirty stocks with the highest trading revenue at the OMX Stockholm exchange (Avanza, 2015). The four companies in the OMXS30 index producing commodities; Boliden (non-ferrous metals), Lundin Petroleum (crude oil), SCA (forestry products) and SSAB (steel), together made up for 6.67 % of the index on November 2 2015. When adding Sandvik and Atlas Copco, two companies partly producing products for the mining and forestry industry, the percentage increases to 16.56 % (NasdaqOMX, 2015). Several other companies that make up the OMXS30 index use commodities in their production. OMXS30 is therefore direct and indirect, linked to the prices of commodities to a high degree.

To further test the predictability, a few companies traded on the Scandinavian stock markets will be used and tested against the different commodity indices. The companies are chosen because they have some kind of relationship to the different commodity indices used and because they have been publicly quoted during the entire time period used. The purpose is to see if certain commodity indices predict certain stocks better. For example if the LME index predicts future Boliden stock returns better than the it predicts future HM stock returns. Since Boliden produces mostly non-ferrous metals (Boliden, 2015) while HM sells clothes, there should be differences and LME should be a better predictor for Boliden than HM if it is possible to predict stock returns to a certain degree.

The other companies used are:

* Atlas Copco, a Swedish company producing tools and equipment for the mining, construction and industrial sectors (Atlas Copco, 2015).
* Holmen, a forestry group owning forests, producing paper, paperboard, sawn timber and renewable energy from forestry products and windfarms on their land (Holmen, 2015).
* Maersk, a Danish conglomerate owning and getting most of its revenue from Maersk Line, the world's largest shipping company (Maersk, 2015).
* Sandvik, a company producing tools for metal cutting, tools for the construction and mining sector as well as different products in advanced materials like special alloys and titanium (Sandvik, 2015).
* SCA, also a forestry company, but they have focused more on diversification than Holmen and therefore produces a wider variety of products from forests raw materials like personal hygiene

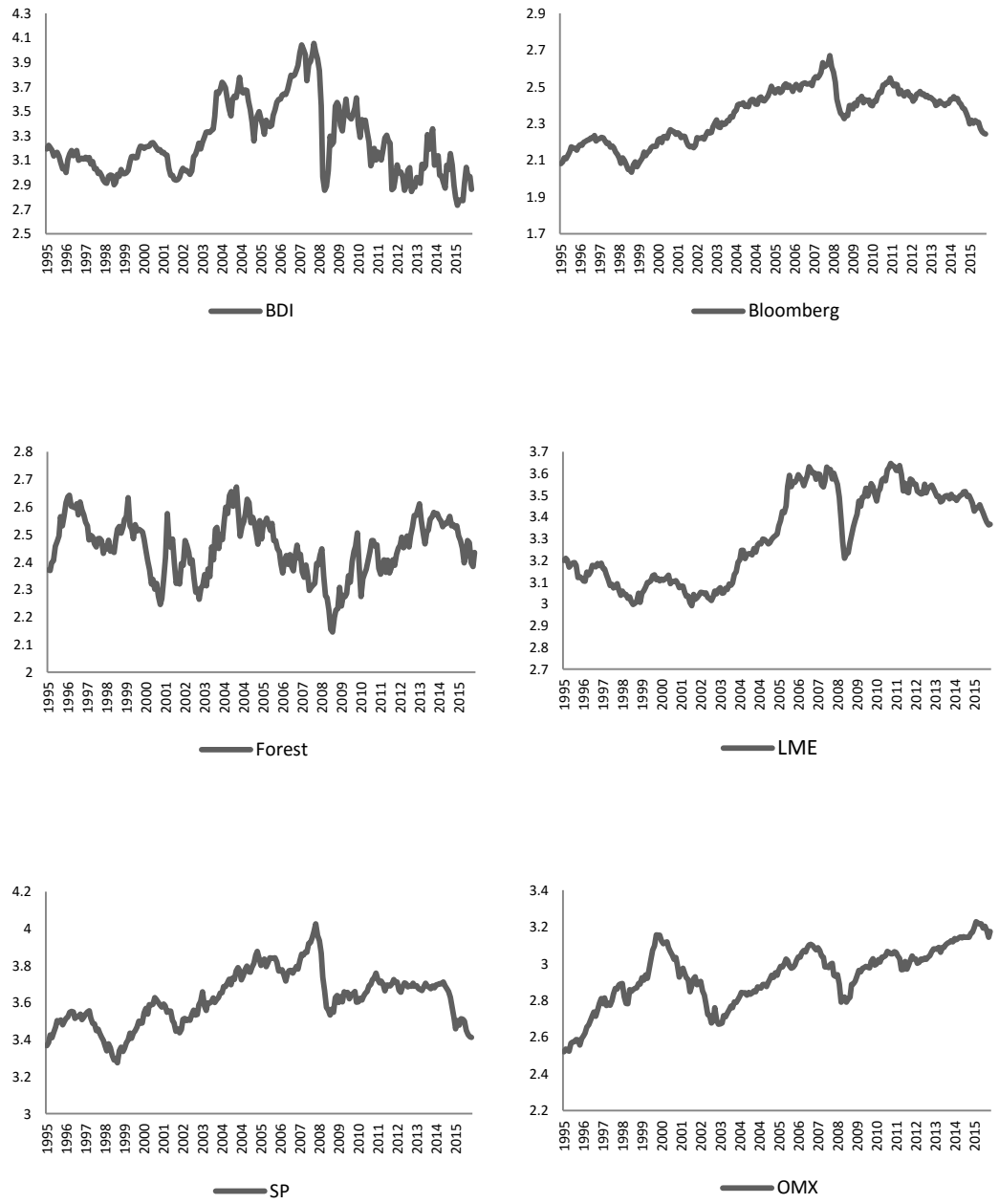
products (SCA, 2015).

* SSAB, steel producer producing different kind of steel products (SSAB, 2015).

To test the robustness of the predictions, financial and macroeconomic variables will be added to the predictions in a later stage. The financial variables are the price-earnings ratio (PE) which is the total market value of the company divided with the total earnings and the dividend yield (DY) which is the total dividend divided with the total market value. Both PE and DY used in this thesis are for the OMX Stockholm 30 index. The last financial variable is the MCSI World which contains large and mid cap stocks across 23 developed countries (including Sweden and Denmark). The index covers roughly 85 % of the market capitalisation is each country (MCSI, 2016). The macroeconomic variable used is the total export for Sweden.

Below in Diagram 2 are the five commodity indices used as predictors and the OMX index displayed.

Diagram 2 – Descriptive data



3.2. Data testing

3.2.1. Unit root test

Before the prediction regressions can be estimated the time series used need to be tested for a unit root. The testing is performed in order to make sure that the data is stationary. If the data is not stationary, there is a risk that the regressions will not be valid because of spurious t-distributions resulting in wrongful p-values, infinite persistence in shocks and spurious regressions where the R^2 value signals an artificially high level of predictability. The unit root tests are performed using the Augmented Dicky-Fuller test (hereafter ADF) which is the most commonly used unit root test. The Schwarz information criterion (SIC) is used in order to determine the optimal number of lags in the ADF test. Each time series will first be tested using an added individual intercept and a second time adding both intercept and a time trend. The reason for adding an intercept respectively a time trend is to smoothen out the data if necessary and therefore get a better fit. ADF assumes a null hypothesis of a unit root, i.e. the time series is non-stationary.

As shown in Appendix 1, all time series used in this thesis are stationary down to a 1 % significance level for the one month commodity returns and the three months commodity return rate. Removing the time trend has no effect on the end result. When testing for the accumulated six months commodity returns, the results start to differ slightly in significance. But at a 5 % level the null hypothesis of a unit root can be rejected for all time series besides Bloomberg with added individual intercept and time trend where the null hypothesis can't be rejected even at a 10 % level. Though since the test specification with only an intercept can be rejected at a 5 % level, Bloomberg will be considered stationary in the rest of the thesis. All the stock returns and all the financial macro data are significant at all significance levels.

3.2.2. Correlation test

The test for correlation is done to make sure that there is no multicollinearity between the explanatory variables. As shown in Appendix 2 there is no correlation between any commodity return time series and macroeconomic or financial variable that will be used in the analysis. Forest and Exports has the highest correlation with 0.42 but that is not to be considered high. There is therefore no reason to suspect multicollinearity between any of the used time series.

3.3. Model used

The following model will be used in this thesis for the in sample prediction:

$$Stock\ return_{t+1} = \alpha + \beta Commodity\ return_t + \gamma Financial\ economic\ variables_t + \varepsilon_{t+1}$$

Previous research by including Goyal and Welch (2007), Bakshi et al (2011), Jacobsen et al (2014) and Zhang et al (2015) have showed that OLS can be used for in-sample prediction if the data used fulfills the requirements of no persistence. Therefore there is no reason to use anything else than an OLS model in this thesis. Newey-West standard errors will be used for all predictions in order to make sure that the model can be used for prediction and that persistence in the data does not cause any problems with wrongful t-statistics and because of that display incorrect p-values.

The commodity returns are in the form of $(Return_t/Return_{t-k})$ where k decides the length of the return period. This paper will use three different return period windows, one month $(Return_t/Return_{t-1})$, three months $(Return_t/Return_{t-3})$ and six months $(Return_t/Return_{t-6})$. In essence, a six month return period is the growth in the return over a six month period. Campbell and Shiller (1988) proved that there is a significant advantage in having predictors with as low variance as possible, and a way to achieve that is according to Bakshi et al (2011) to use longer return periods. They argue that by using a longer period (in their case three months) certain seasonality and commodity forward contracts resulting in market lags etcetera will be included in a better way. The other reason is to implement the commodity derivative contracts that could be longer than just a month. For the reasons mentioned above, the three chosen return periods will be tested initially to see if there is any difference in the predictability when using the different return periods.

In the first step of in-sample prediction, the stock returns will be predicted using only the different commodity returns. Then in the next step financial and macroeconomic variables will be added to the prediction model to see if a; the adjusted R-squared prediction results get better and b; to see if the p-values of the β-coefficients still are significant.

3.4. In-sample prediction

3.4.1. Predictability of stock returns – one period commodity return rate

The first step in the testing of the predictability will be done using one period commodity returns in the following econometrical model:

$$Stock\ return_{t+1} = \alpha + \beta Commodity\ return_t + \varepsilon_{t+1}$$

Where $\text{Stock return}_{t+1} = (\text{Return}_{t+1}/\text{Return}_t)$, α is the intercept, $\text{Commodity return}_t = (\text{Return}_t/\text{Return}_{t-1})$ and ε_{t+1} is the residual. The model will be used one time for each separate commodity index.

Table 1 – One period commodity return rate predictions

Dependent variable: OMX
Time period: Oct 1995 - Oct 2015
Observations: 240 (monthly)

Variable	β-value	STD-Div	P-value	DW	Adj R-square
BDI	0.031	0.021	(0.129)	1.833	0.50%
Bloomberg	0.174	0.066	(0.009)***	1.824	2.40%
Forest	0.066	0.032	(0.039)**	1.867	1.40%
LME	0.401	0.068	(0.000)***	1.909	12.30%
SP	0.118	0.071	(0.090)*	1.892	0.70%

1. Significance levels: * = 10 %, ** = 5 %, *** = 1 %
2. DW = Durbin-Watson statistic

The values from the one period lagged prediction of OMX are presented above in Table 1. LME has the best predictability with an adjusted R^2 of 12.3 % meaning that in this regression 12.3 % of the return in the OMX index comes from LME. The beta-coefficient of 0.4 means that on average during the time period of the series (Oct 1995 to Oct 2015), an increase in LME by 1 % increased OMX with 0.4 %. The p-value also shows that the null hypothesis of no significance can be rejected down to a 0.1 % level. The second best adjusted R^2 is achieved by the Bloomberg index with 2.4 % and a beta-coefficient of 0.17. Forest has a very low predictability level but the variable is significant down to a 5 % level. SP and BDI both have low adjusted R^2 values and bad significance levels. Therefore they cannot be considered useful predictors for OMX in this specification. From the DW values, no signs of autocorrelation can be seen in any of the predictions.

The predictions of stock returns for the specific companies are presented in Appendix 3. The result of using Boliden against LME is highly interesting with an adjusted R^2 of 14.7 % and a beta-coefficient of 1.95. As mentioned in the Data section, Boliden produces mostly non-ferrous metals which also are what make up the LME index. In general LME is the best predictor for five out of eight companies used in the testing of the one period ahead predictability using the one month commodity return rate. It is also worth noticing that BDI has a low predictability of Maersk which is interesting considered that the Maersk conglomerate is mainly made up of a shipping company. Instead the two broad commodity indices Bloomberg and SP have the highest level of predictability for Maersk with adjusted R^2 of 8.2 % respectively 6.6 % of the tested stocks. Potential reasons for the lack of predictability that BDI shows of the Maersk stock returns could be that Maersk is mostly doing container shipping and not dry bulk and also that certain years, Maersk has sourced the majority of their profits from their other holdings in oil, drilling and oil service, crude oil tankers and terminal

services (Maersk, 2015). Therefore it makes sense that the more general indices Bloomberg and SP that also contain the price of oil predict Maersk the best in this test.

The forestry company Holmen does not show any p-values of under 0.1 (the required level for not being rejected at the highest 10 % significance level). The other forestry company SCA does, but Forest has the lowest level of predictability of the commodity indices used. SCA sources over 90 % of their profits from other sources than timber and pure forestry products. Also the Forestry index used in this thesis is American while SCA and Holmen sell the majority of their timber to Europe, North Africa and to the Middle East and that could be a reason for the low level of predictability of Forest on SCA (Holmen, 2015; SCA, 2015). Because of the lack of significance and predictability, Forest has to be considered a bad predictor of the return of both Holmen and SCA.

The two industrial companies Atlas Copco and Sandvik both have LME, SP and Bloomberg as their three best predictors. Since both companies work mostly in producing tools from and for metal this seems correct. The fact that using LME as a predictor of SSAB returns an adjusted R^2 of 12.8 % and a beta-coefficient of 1.24, shows the strong impact that metal prices have on several of the companies being predicted in this thesis.

3.4.2. Predictability of stock returns – three and six periods commodity return rate

The same econometrical model as in the one period growth rate window will be used. The only difference is that the commodity return will go from using one period returns to using a three period and a six period return period to predict the stock returns: $\text{Commodity return}_t = (\text{Return}_t/\text{Return}_{t-3})$ respective $(\text{Return}_t/\text{Return}_{t-6})$.

Table 2 – Three periods commodity return rate predictions

Dependent variable: OMX
Time period: Oct 1995 - Oct 2015
Observations: 238 (monthly)

Variable	β-value	STD-Div	P-value	DW	Adj R-square
BDI	0.022	0.011	(0.042)**	1.841	0.40%
Bloomberg	0.070	0.035	(0.049)**	1.831	1.20%
Forest	0.025	0.019	(0.187)	1.836	0.30%
LME	0.131	0.036	(0.000)***	1.894	4.90%
SP	0.040	0.037	(0.275)	1.818	0.00%

1. Significance levels: * = 10 %, ** = 5 %, *** = 1 %
2. DW = Durbin-Watson statistic

As shown in Table 2 above and in Appendix 3, the predictability decreases when we increase the commodity return rate window. The only positive change compared to the one period prediction is that BDI now is significant at a 5 % level. SP and Forest on the other hand lose their significance even at a 10 % level. The beta-values and the adjusted R^2 go down for all variables.

Table 3 – Six periods commodity return rate predictions

Dependent variable: OMX
Time period: Oct 1995 - Oct 2015
Observations: 235 (Monthly)

Variable	β-value	STD-Div	P-value	DW	Adj R-square
BDI	0.007	0.006	(0.294)	1.833	0.00%
Bloomberg	NEG	0.008	(0.647)	1.801	NEG
Forest	0.000	0.000	(0.955)	1.809	0.00%
LME	0.002	0.008	(0.776)	1.814	0.00%
SP	NEG	0.008	(0.419)	1.799	NEG

1. Significance levels: * = 10 %, ** = 5 %, *** = 1 %
2. DW = Durbin-Watson statistic

Now all the variables lack significance at any used level and the adjusted R^2 is either negative (presented as NEG in the tables) or too low to be considered. Therefore using six periods return rate has to be considered useless for prediction and will not be considered when testing for predictability with added financial variables. The result is the same for the individual stocks where no prediction is significant and the result from the individual stock prediction will therefore not be presented.

3.4.3. Predictability of stock returns with added macro variables – one period commodity return

By adding more potential predictors to the model, the actual robustness of the predictability link between the predictor and predicted variable can be tested (Guidolin and Timmermann, 2006; Gargano and Timmermann, 2013). Therefore the price-earnings ratio (hereafter PE), dividend yield (hereafter DY) and export will be added to the prediction model in a first step. The PE and DY are for the OMXS30 index and the export is for Sweden. This is worth noticing since Maersk is a Danish and not Swedish company. In the second step the one period returns of the MCSI World index (hereafter MCSI) will be added to the prediction model. Previous research done by Harvey (1995) has proved that MCSI is a useful predictor of stock returns.

The result is presented in Appendix 4. In general the predictability stays robust when adding the financial variables. Only SP goes from being significant at a 10 % level to not being significant when the MCSI is added to the model. Otherwise all indices stay at their significance level. For Forest and

LME the difference in beta-coefficients, p-values and the adjusted R^2 are minor, but for Bloomberg the result improves where adjusted R^2 goes from 2.4 % to 4 % when the MCSI is added and to 4.02 % when the financial macro variables are added.

Worth noticing is that DY and PE both have negative beta-coefficients and that PE and Export never are significant while DY is significant together with all used predictors except LME. The negative beta-coefficient for the dividend yield means that a higher percent of dividend compared to the stock value negatively affects the predicted return. The negative beta-coefficients of DY confirm the result from predictive regressions done by Goyal and Welch (2007).

While the financial variables in several tests are not significant, the MCSI stays significant in all tests where the tested predictor also is significant. This confirms the result of Harvey (1995).

3.4.4. Predictability of stock returns with added financial variables – three periods commodity return

Since the six period predictors lacked significance, they will not be used in testing for predictability with added financial variables. The results are presented in Appendix 4.

BDI follows the same pattern with added variables as it does without them. With the three period growth rate window BDI is significant at a 5 % level, but not significant at even a 10 % level when using the one period returns. The adjusted R^2 improves though and goes from 1.2 % to 1.67 % when adding financial macro variables and increases to 2.37 % when adding MCSI. Forest and LME also improve slightly while Bloomberg and SP fail to make any improvements in significance levels or predictability.

The result from using added variables both in the one and the three period predictability model strengthens the conclusion that the predictors that earlier have proved to be robust survive having alternative variables added to them which is favorable and a sign that the predictors work.

3.4.5. Predictability of stock returns three and six periods ahead

When predicting stock returns three (t+3) and six months ahead (t+6), there is no significance in any of the predictors at even a 10 % level. When adding financial variables the result improves and some predictors are now significant at a 5 % level. Though, since they initially are not significant, they will not be considered useful for longer predictions than predictions one month ahead.

3.4.6. Predictability using several commodity indices.

Even though this thesis mainly focuses on using one commodity index at a time as predictor of stock returns, in-sample predictions using several commodity indices at the same time will be executed too. The idea behind adding more commodities as predictors is to see if it is possible to get a higher predictability while still keeping the predictors significant. Because of the high correlation between Bloomberg and SP, only Bloomberg will be used to limit the risk of multicollinearity. Bloomberg is chosen simply because it has performed better.

The results are presented in Appendix 5. The one period commodity returns were used since they have performed the best. The results show that by using several commodity indices as predictors at the same time, it is possible to achieve a better predictability. The best predictor for OMX using only one predictor was LME with an adjusted R^2 of 12.3 %. When all four predictors are used, the adjusted R^2 increases to 13.3 %. Only LME and Forest are significant however. For the individual stocks, the adjusted R^2 increase for six out of eight compared to using the best single predictor for each stock. Boliden has the highest increase and gets an adjusted R^2 of 22 % with Bloomberg, Forest and LME all being significant. The value of 22 % is so high however compared to previous research that it is worth questioning if it could be something wrong in the model specification giving biased result. For Holmen and HM the predictability link does not exist for any of the two stocks since the adjusted R^2 is negative.

A correlations test between the financial variables and the commodity indices showed very low rates of correlation (never over 0.11 or under -0.1). Tests with added financial variables were therefore also made. However the general changes compared to just using the four commodity indices were too small to even be considered since the financial variables did not become significant at even a 10 % level in any of the tests. MCSI got significant only for Boliden where the adjusted R^2 increased to 23 %. Because of the low significance, the results will not be presented in detail.

The good results from using several commodity indices as predictors at the same time add more proof to the predictability of stocks that commodities show.

3.5. Out-of-sample prediction

The usability of out-of-sample prediction of stock returns is the same as for using added financial and macroeconomic variables, in essence to impose more hurdles and test the actual robustness of the predictability link. An out-of-sample result similar to the in-sample result is a sign that the in-sample result is accurate (Goyal and Welch, 2008). An investor looking to use the ideas in this thesis will most likely use out-of-sample predictions since investors are interested in predicting the future and

not just look back in-sample. This itself adds to the motivation to use out-of-sample predictions in this thesis.

For the out-of-sample prediction, the method of calculating out-of-sample R^2 (hereafter R^2_{OOS}) used by Campbell and Thompson (2007), Goyal and Welch (2008), Black et al (2014), Jacobsen et al (2014) among others will be used to measure the quality of the predictions. R^2_{OOS} is calculated as follows:

$$R^2_{OOS} = 1 - \frac{MSE_{Prediction}}{MSE_{Actual}} = 1 - \frac{\sum_{t=1}^{T}(r_t - \widehat{r_t})}{\sum_{t=1}^{T}(r_t - \overline{r_t})}$$

r_t is the actual return, $\widehat{r_t}$ is the fitted prediction for the return the same period and $\overline{r_t}$ is the average actual return. The reason for calculating the R^2_{OOS} is to make it easy to compare the out-of-sample results with the result from the in-sample predictions where the adjusted R^2 was used as a measurement of the predictability. Another benefit of using R^2_{OOS} is its ability to show if a return series is truly unpredictable. If the R^2_{OOS} is negative, then the return series can be ruled out as not being significant and therefore unpredictable (Campbell and Thompson, 2007). The opposite is also true. A positive R^2_{OOS} indicates the existence of a predictor. The reason is simply that a lower mean squared prediction error ($MSE_{Prediction}$) compared to the mean squared error from the actual return with the average subtracted (MSE_{Actual}) gives a positive R^2_{OOS}.

The out-of-sample predictions are one period ahead and in the form of expanding window with an initial window of 200 and 120 months (half the sample) and rolling forecasts with a time window of 200 and 120. Because of Boliden's lower number of observations, it will use a time window of 160 and 100 months instead. Expanding windows have the advantage of covering all possible data while the rolling windows have an advantage if the prediction estimator happens to be misspecified in some way. The usage of rolling windows excludes older data that might interfere or no longer be useful. Another advantage of using rolling windows is that they better incorporate time variations in the used parameters like potential breaks caused by events occurring on the market (Giacomini and White, 2006).

As shown in Appendix 6, the out-of-sample predictions follow previous patterns where commodity indices that performed well as predictors for certain stocks during in-sample prediction perform well in the out-of-sample prediction too. However, the general pattern is that the out-of-sample prediction performed better than the in-sample prediction when using a 200 months expanding window. In 32 out of 45 out-of-sample regressions the results were better than in the in-sample regressions. In the other three out-of-sample prediction specifications, the results were lower than for the best in-sample predictions.

If using the criteria that three or four negative R^2_{OOS} values per predictor used on OMX or a specific stock means that the predictor fails in that circumstance and therefore that the stock return cannot be predicted using that commodity index. Then BDI fails to predict eight out of nine times in this test. BDI therefore has to be considered a bad predictor. HM cannot be predicted out-of-sample by any of the used indices and for both the two forestry companies Holmen and SCA, only LME can predict and that with R^2_{OOS} values not exceeding 2.2 %. LME continues to be a good predictor even out-of-sample giving OMX a R^2_{OOS} of 12.59 %, Boliden a R^2_{OOS} of 13.98 % and SSAB a R^2_{OOS} of 13.14 % when using a 200 month expanding window.

3.5.1. Adjusted Mean Squared Prediction Error from out-of-sample predictions

To further prove the robustness of the out-of-sample predictions using commodities as predictors, the p-values from the adjusted Mean Squared Prediction Error (hereafter adj-MSPE) as suggested by Clark and West (2007) and Bakshi et al (2011) will be calculated. The idea is to test the out-of-sample predictions against the theory that the returns just follow a random walk (as suggested by the EMH). The adj-MSPE will be calculated as follows:

$$AdjMSPE = \left(r_{t+1} - \widehat{r_{t+1,RW}}\right)^2 - \left(r_{t+1} - \widehat{r_{t+1,OOS}}\right)^2 - \left(\widehat{r_{t+1,RW}} - \widehat{r_{t+1,OOS}}\right)^2$$

Where r_{t+1} is the actual return, $\widehat{r_{t+1,RW}}$ is the Random Walk return where the lagged actual return is used to predict the return according to: $r_{t+1} = r_t + drift$ and $\widehat{r_{t+1,OOS}}$ is the out-of-sample prediction one period ahead. Since using a 200 month expanding window gave the best result, the predictions from that specification will be used here too. The adj-MSPE will then be regressed on a constant to get the t-stat and p-value (Bakshi et al, 2011).

P-values from the adj-MSPE will be calculated for the main index OMX and for Boliden since Boliden performed best of the eight stocks in the out-of-sample prediction measured by the R^2_{OOS}. The results are presented below in Table 4.

Table 4 – P-values from the adj-MSPE

Dependent V	Variable	P-value
OMX	BDI	(0.029)**
	Bloomberg	(0.001)***
	Forest	(0.215)
	LME	(0.000)***
	SP	(0.143)
Boliden	BDI	(0.022)**
	Bloomberg	(0.021)**

Forest	(0.000)***
LME	(0.009)***
SP	(0.016)**

The results conclude that Bloomberg and LME are good predictors of OMX one period ahead. Forest and SP did not perform well out-of-sample for OMX which also shows in the p-values from the Adj-MSPE. BDI is significant at a 5 % level but not a 1 % level which also seems reasonable considering the result that BDI performed on OMX. For Boliden the two best predictors when using the 200 months expanding window is LME and Forest. Both indices are significant down to a 1 % level. BDI, Bloomberg and SP got positive R^2_{OOS} and are also significant when predicting Boliden but on a 5 % level.

Summary of the results from the empirical analysis

Bakshi et al (2011) found that the return of BDI can explain the return of certain general stock indices up to a 9 % level depending on model specification and number of lags used, though for most stock indices the level is between 1-4 % for in sample predictions and slightly higher for out-of-sample predictions. BDI is the index that has performed the worst as a predictor in this thesis both in and out-of-sample. Since a negative R^2_{OOS} is a sign that the predictor cannot predict sufficiently, BDI has to be considered useless for predicting most of the stocks in this thesis. A possible explanation is that BDI has as of 12 of January 2016 dropped to its lowest notation since the index was founded in 1985 while the Swedish stock market has not followed in the same down spiral. It therefore seems natural that the predictability has decreased in the last years.

LME performs well throughout the predictions and is the strongest predictor. The good result of LME as a predictor conforms the result of Jacobsen et al (2014) where they got a R^2_{OOS} of as high as 9 % when using different metal indices as predictors of the return of broader stock indices. In this thesis LME predicts OMX the strongest of all five indices no matter specification of the prediction both in and out-of-sample. LME also predicts Boliden and SSAB the highest and LME stays robust even with added financial variables or when used together with other commodity indices as joint predictors. When predicting OMX one period ahead the adjusted R^2 stays over 12 % no matter specification as long as one month growth rate is used. The result is therefore both strong and robust in favor of predictability.

SP and Bloomberg perform similar in some cases and not very similar in other cases. Throughout the predictions Bloomberg performs better than SP in all cases except for the out-of-sample predicting of HM where SP is better with 0.07 % higher R^2_{OOS} which has to be considered to be within the error

margin. The reason why Bloomberg performs better could be that SP has fallen more the last few years since it is heavier weighted towards energy prices that have been falling and that SP also has had a higher volatility with 0.014 compared to 0.007 since the financial crises for both logged series. Over the whole time period both indices has a nearly identical volatility with 0.0209 for Bloomberg and 0.0216 for SP. Both indices perform better when financial variables are added showing that they stand up even when more variables are added. Bloomberg does not perform very well together with other commodity indices however and only managed to stay significant when predicting three out of nine times.

Forest performs steady throughout the thesis and usually stays in the 1-3 % predictability range with 7.3 % for Boliden being the only exception. However the index does not perform well for any of the two forestry companies used.

4. Conclusions

The Efficient Market Hypothesis (EMH) states that it should not be possible to predict stocks since the market is efficient. This thesis proves using several different tests that the hypothesis does not hold. OMX shows proof of being able to be partly predicted using commodity indices even if the link between the commodity returns and the stock returns is not always direct at first glimpse. Individual stocks show either an even higher level of predictability or a lower predictability than OMX. The result is stronger for some indices that relate to what the companies produce. The LME index predicts and forecasts the mining company Boliden and the steel producer SSAB best and the toolmakers Atlas Copco and Sandvik are together with the shipping conglomerate Maersk best predicted using the two general commodity indices Bloomberg and SP. However, there exists no prediction link between the forestry index and the two forestry companies Holmen and SCA. HM, which is the biggest company used in the analysis in terms of market capitalisation does not show a prediction link at all.

The question one has to ask is if the level of predictability proved in this thesis actually is strong enough to give an investor an advantage when investing. A predictability of as much as 14 % using a single commodity index as predictor will give an investor a big edge when it comes to investments, but one or two percent will probably not, or at least not to the same extent. However the result still proves that a robust predictability link exists. Also the fact that the predictions only worked one period ahead is worth noticing. Still, the thesis has proved that it is possible to predict stock returns and that is proof that the EMH does not hold.

A possibility for further research and development of the prediction model could be to include more commodities related to certain stocks or markets. An example is to add gold and silver returns besides the LME index when predicting Boliden since Boliden produces precious metals too, besides the non-ferrous metals. Another possible continuation could be to add more companies and more commodity indices or pure commodities. For example test the predictability of cotton on HM or the predictability of cocoa on the Swedish confectionary company Cloetta. Also to use the Adjusted Mean Squared Prediction Error p-value to test and hopefully prove the predictability of the commodity indices further is a good way forward. The use of commodities as predictors of stock returns is still an academic field that has a lot more potential to be researched. Especially considered the research by Basak and Pavlova (2013) showing that the correlation between commodities and stocks will increase in general over time because of the new trading patterns of commodities.

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Appendix 1 – Unit root testing

	Individual intercept and trend		Individual Intercept	
	ADF T-stat	ADF P-value	ADF T-stat	ADF P-value
Bloomberg t-1	-14.30866	(0.000)***	-14.11515	(0.000)***
Bloomberg t-3	-6.148479	(0.000)***	-5.960435	(0.000)***
Bloomberg t-6	-3.136112	(0.101)	-2.909099	(0.046)**
BDI t-1	-13.54550	(0.000)***	-13.56712	(0.000)***
BDI t-3	-6.052330	(0.000)***	-5.997537	(0.000)***
BDI t-6	-4.17802	(0.006)***	-4.0686	(0.001)***
LME t-1	-13.16204	(0.000)***	-13.18866	(0.000)***
LME t-3	-5.013084	(0.000)***	-5.015191	(0.000)***
LME t-6	-3.455791	(0.047)**	-3.445774	(0.010)**
Forest t-1	-16.38382	(0.000)***	-16.41374	(0.000)***
Forest t-3	-7.661232	(0.000)***	-7.680831	(0.000)***
Forest t-6	-4.253418	(0.004)***	-4.242186	(0.001)***
SP t-1	-13.40109	(0.000)***	-13.27712	(0.000)***
SP t-3	-4.714454	(0.001)***	-4.593064	(0.000)***
SP t-6	-3.627953	(0.029)**	-3.448072	(0.010)**
OMX	-14.04187	(0.000)***	-14.03348	(0.000)***
Boliden	-10.87793	(0.000)***	-10.84635	(0.000)***
Maersk	-15.09282	(0.000)***	-15.02463	(0.000)***
Holmen	-16.68419	(0.000)***	-16.71271	(0.000)***
HM	-16.06313	(0.000)***	-15.44491	(0.000)***
SSAB	-9.072895	(0.000)***	-8.944459	(0.000)***
Atlas Copco	-16.55083	(0.000)***	-16.53790	(0.000)***
SCA	-15.83966	(0.000)***	-15.86578	(0.000)***
PE	-14.07248	(0.000)***	-14.09636	(0.000)***
DY	-12.40983	(0.000)***	-12.43475	(0.000)***
Export	-16.5979	(0.000)***	-16.56618	(0.000)***
MCSI	-14.6861	(0.000)***	-14.71827	(0.000)***

Significance levels: ** = 5 %, *** = 1 %

Appendix 2 – Correlation table

	PE	DY	Export	MCSI
Bloomberg t-1	-0.040	0.082	0.191	-0.012
Bloomberg t-3	0.006	0.026	0.373	0.055
Bloomberg t-6	-0.051	0.061	0.398	0.053
BDI t-1	0.030	-0.078	-0.023	0.104
BDI t-3	0.146	-0.098	0.203	0.190
BDI t-6	0.074	-0.017	0.236	0.142
LME t-1	-0.026	0.056	0.016	0.054
LME t-3	-0.084	0.049	0.049	-0.017
LME t-6	-0.017	0.019	0.091	0.030
Forest t-1	-0.035	-0.003	0.243	0.015
Forest t-3	0.011	-0.013	0.421	0.126
Forest t-6	0.002	-0.027	0.413	0.137
SP t-1	-0.081	0.134	0.250	-0.023
SP t-3	-0.022	0.044	0.387	0.015
SP t-6	-0.080	0.093	0.385	-0.006

Appendix 3 – Individual stocks

Individual stocks predicted using the commodity indices. NEG means that the Adjusted R-square is negative and therefore has no prediction power.

One month commodity return rate
240 Observations per variable
(200 for Boliden)

Time period: Oct 1995 - Oct 2015

Dependent V	Variable	β-value	STD-Div	P-value	DW	Adj R-square
Atlas Copco	BDI	0.053	0.055	(0.338)	2.145	NEG
	Bloomberg	0.621	0.174	(0.000)***	2.245	4.68%
	Forest	0.218	0.085	(0.011)**	2.178	2.31%
	LME	0.731	0.190	(0.000)***	2.301	5.49%
	SP	0.524	0.189	(0.006)***	2.202	2.74%
Boliden	BDI	0.171	0.095	(0.074)*	1.566	1.13%
	Bloomberg	0.791	0.329	(0.017)**	1.576	2.38%
	Forest	0.596	0.147	(0.000)***	1.569	7.31%
	LME	1.947	0.331	(0.000)***	1.824	14.67%
	SP	0.812	0.351	(0.022)**	1.554	2.17%

Holmen	BDI	-0.015	0.036	(0.670)	2.135	NEG
	Bloomberg	0.098	0.118	(0.404)	2.143	NEG
	Forest	-0.001	0.057	(0.992)	2.133	NEG
	LME	0.225	0.128	(0.081)	2.174	0.86%
	SP	-0.010	0.127	(0.938)	2.132	NEG
HM	BDI	0.022	0.045	(0.634)	1.978	NEG
	Bloomberg	0.093	0.147	(0.529)	1.966	NEG
	Forest	0.066	0.070	(0.351)	1.985	NEG
	LME	0.216	0.160	(0.177)	1.970	0.35%
	SP	0.118	0.157	(0.465)	1.966	NEG
Maersk	BDI	0.050	0.025	(0.051)*	1.966	1.18%
	Bloomberg	0.374	0.079	(0.000)***	2.050	8.21%
	Forest	0.092	0.039	(0.021)**	1.989	1.82%
	LME	0.333	0.088	(0.000)***	2.066	5.30%
	SP	0.362	0.086	(0.000)***	2.044	6.60%
Sandvik	BDI	0.049	0.052	(0.343)	2.113	NEG
	Bloomberg	0.638	0.164	(0.000)***	2.256	5.60%
	Forest	0.129	0.081	(0.110)	2.123	0.65%
	LME	0.722	0.179	(0.000)***	2.328	6.04%
	SP	0.636	0.176	(0.000)***	2.219	4.78%
SCA	BDI	0.031	0.038	(0.421)	2.053	NEG
	Bloomberg	0.214	0.123	(0.083)*	2.085	0.84%
	Forest	0.065	0.059	(0.276)	2.067	0.08%
	LME	0.315	0.133	(0.019)**	2.123	1.88%
	SP	0.181	0.132	(0.172)	2.069	0.37%
SSAB	BDI	0.030	0.063	(0.631)	1.957	NEG
	Bloomberg	0.857	0.196	(0.000)***	2.150	7.07%
	Forest	0.232	0.096	(0.017)**	2.015	1.96%
	LME	1.246	0.207	(0.000)***	2.281	12.82%
	SP	0.792	0.212	(0.000)***	2.119	5.14%

1. Significance levels: * = 10 %, ** = 5 %, *** = 1 %
2. DW = Durbin-Watson statistic

Three months commodity
return rate
240 Observations per variable
(200 for Boliden)

Time period: Oct 1995 - Oct 2015

Dependent V	Variable	β-value	STD-Div	P-value	DW	Adj R-square
Atlas Copco	BDI	0.027	0.031	(0.380)	2.149	NEG
	Bloomberg	0.219	0.094	(0.020)**	2.202	1.84%
	Forest	0.143	0.050	(0.005)***	2.175	2.95%

	LME	0.274	0.097	(0.005)***	2.230	2.86%
	SP	0.166	0.098	(0.090)*	2.172	0.79%
Boliden	BDI	0.162	0.052	(0.002)***	1.583	4.24%
	Bloomberg	0.241	0.175	(0.169)	1.528	0.46%
	Forest	0.293	0.089	(0.001)***	1.519	4.81%
	LME	0.883	0.166	(0.000)***	1.708	12.17%
	SP	0.113	0.181	(0.532)	1.512	NEG
Holmen	BDI	-0.001	0.020	(0.968)	2.163	NEG
	Bloomberg	0.049	0.062	(0.429)	2.171	NEG
	Forest	0.040	0.033	(0.230)	2.161	0.19%
	LME	0.123	0.064	(0.056)*	2.203	1.13%
	SP	0.033	0.064	(0.603)	2.166	NEG
HM	BDI	0.000	0.025	(0.990)	2.013	NEG
	Bloomberg	0.037	0.078	(0.636)	2.009	NEG
	Forest	0.060	0.041	(0.150)	2.026	0.46%
	LME	0.013	0.081	(0.869)	2.012	NEG
	SP	0.003	0.080	(0.971)	2.012	NEG
Maersk	BDI	0.024	0.014	(0.091)*	1.976	0.78%
	Bloomberg	0.133	0.043	(0.002)***	2.029	3.42%
	Forest	0.062	0.023	(0.008)***	1.984	2.53%
	LME	0.150	0.045	(0.001)***	2.048	4.09%
	SP	0.110	0.045	(0.015)**	2.009	2.06%
Sandvik	BDI	0.043	0.029	(0.141)	2.132	0.49%
	Bloomberg	0.307	0.087	(0.001)***	2.239	4.55%
	Forest	0.110	0.048	(0.021)**	2.139	1.82%
	LME	0.339	0.091	(0.000)***	2.278	5.19%
	SP	0.280	0.091	(0.002)***	2.194	3.44%
SCA	BDI	0.004	0.021	(0.831)	2.076	NEG
	Bloomberg	0.060	0.065	(0.357)	2.087	NEG
	Forest	0.052	0.035	(0.136)	2.087	0.52%
	LME	0.095	0.067	(0.157)	2.104	0.43%
	SP	0.013	0.067	(0.843)	2.074	NEG
SSAB	BDI	0.054	0.035	(0.122)	1.983	0.59%
	Bloomberg	0.391	0.105	(0.000)***	2.092	5.11%
	Forest	0.131	0.057	(0.023)**	1.986	1.76%
	LME	0.530	0.107	(0.000)***	2.148	8.98%
	SP	0.310	0.110	(0.006)***	2.040	2.81%

1. Significance levels: * = 10 %, ** = 5 %, *** = 1 %
2. DW = Durbin-Watson statistic

Appendix 4 – Added financial variables

OMX predicted using a commodity index but also with added financial variables.

One month commodity return rate with added financial variables

240 Observations per variable

Time period: Oct 1995 - Oct 2015

Variable	β-value	STD-Div	P-value	DW	Adj R-square
BDI	0.031	0.021	(0.132)	1.930	1.23%
PE	-0.020	0.023	(0.400)		
DY	-0.012	0.007	(0.083)		
Export	0.612	0.522	(0.243)		
BDI	0.029	0.020	(0.158)	1.938	1.98%
MCSI	0.157	0.077	(0.044)**		
Bloomberg	0.174	0.067	(0.010)***	1.927	4.05%
PE	-0.020	0.023	(0.396)		
DY	-0.013	0.007	(0.049)**		
Export	0.353	0.526	(0.503)		
Bloomberg	0.173	0.065	(0.009)***	1.928	4.00%
MCSI	0.170	0.076	(0.027)**		
Forest	0.066	0.032	(0.041)**	1.981	2.05%
PE	-0.020	0.023	(0.388)		
DY	-0.013	0.007	(0.055)*		
Export	0.590	0.520	(0.258)		
Forest	0.059	0.032	(0.062)*	1.973	2.60%
MCSI	0.160	0.077	(0.038)**		
LME	0.400	0.071	(0.000)***	2.003	12.32%
PE	-0.010	0.022	(0.635)		
DY	-0.010	0.006	(0.109)		
Export	-0.122	0.508	(0.811)		
LME	0.395	0.068	(0.000)***	1.989	13.64%
MCSI	0.161	0.072	(0.027)**		
SP	0.119	0.074	(0.108)	1.925	1.37%
PE	-0.019	0.023	(0.409)		
DY	-0.013	0.007	(0.051)*		
Export	0.393	0.537	(0.465)		
SP	0.118	0.071	(0.097)*	1.930	2.30%
MCSI	0.170	0.077	(0.028)**		

1. Significance levels: * = 10 %, ** = 5 %, *** = 1 %

Three months commodity return rate with added financial variables

240 Observations per variable

Time period: Oct 1995 - Oct 2015

Variable	β-value	STD-Div	P-value	DW	Adj R-square
BDI	0.022	0.012	(0.049)**	1.922	1.67%
PE	-0.024	0.023	(0.316)		
DY	-0.012	0.007	(0.073)*		
Export	0.400	0.535	(0.456)		
BDI	0.020	0.012	(0.090)*	1.933	2.37%
MCSI	0.144	0.079	(0.069)*		
Bloomberg	0.062	0.038	(0.104)	1.924	1.37%
PE	-0.019	0.023	(0.429)		
DY	-0.012	0.007	(0.071)*		
Export	0.262	0.564	(0.643)		
Bloomberg	0.063	0.035	(0.076)*	1.937	2.48%
MCSI	0.161	0.077	(0.038)**		
Forest	0.023	0.019	(0.226)	1.945	0.87%
PE	-0.016	0.024	(0.486)		
DY	-0.012	0.007	(0.077)*		
Export	0.567	0.527	(0.283)		
Forest	0.025	0.019	(0.196)	1.954	1.86%
MCSI	0.171	0.077	(0.029)**		
LME	0.137	0.040	(0.001)***	1.973	5.03%
PE	-0.018	0.023	(0.440)		
DY	-0.012	0.007	(0.084)*		
Export	-0.227	0.569	(0.691)		
LME	0.122	0.036	(0.001)***	1.975	5.70%
MCSI	0.137	0.076	(0.075)*		
SP	0.028	0.040	(0.488)	1.918	0.44%
PE	-0.018	0.023	(0.433)		
DY	-0.012	0.007	(0.072)*		
Export	0.448	0.570	(0.432)		
SP	0.036	0.037	(0.325)	1.932	1.56%

MCSI	0.168	0.077	(0.031)**

1. Significance levels: * = 10 %, ** = 5 %, *** = 1 %
2. DW = Durbin-Watson statistic

Appendix 5 - Prediction using several commodity indices

In-sample prediction using several commodity indices at the same time. NEG means that the adjusted R-square was negative.

One month commodity return rate

240 Observations per variable (200 for Boliden)

Time period: Oct 1995 - Oct 2015

Dependent V	Variable	β-value	STD-Div	P-value	DW	Adj R-square
OMX	BDI	0.019	0.022	(0.388)	1.947	13.29%
	Bloomberg	-0.115	0.098	(0.239)		
	Forest	0.053	0.028	(0.055)*		
	LME	0.464	0.116	(0.000)***		
Atlas Copco	BDI	0.012	0.073	(0.869)	2.321	7.23%
	Bloomberg	0.299	0.237	(0.209)		
	Forest	0.188	0.071	(0.009)***		
	LME	0.487	0.259	(0.062)*		
Boliden	BDI	0.122	0.105	(0.248)	1.866	21.93%
	Bloomberg	-0.917	0.408	(0.026)**		
	Forest	0.525	0.157	(0.001)***		
	LME	2.431	0.482	(0.000)***		
Holmen	BDI	-0.022	0.028	(0.437)	2.185	NEG
	Bloomberg	-0.040	0.149	(0.789)		
	Forest	-0.006	0.049	(0.911)		
	LME	0.263	0.132	(0.048)**		
HM	BDI	0.014	0.043	(0.738)	1.983	NEG
	Bloomberg	-0.070	0.197	(0.722)		
	Forest	0.059	0.053	(0.266)		
	LME	0.249	0.238	(0.297)		
Maersk	BDI	0.028	0.026	(0.283)	2.085	9.53%
	Bloomberg	0.278	0.090	(0.002)***		
	Forest	0.073	0.039	(0.064)*		
	LME	0.116	0.119	(0.333)		
Sandvik	BDI	0.010	0.074	(0.888)	2.345	6.70%
	Bloomberg	0.348	0.203	(0.088)*		

	Forest	0.098	0.071	(0.169)		
	LME	0.460	0.191	(0.017)**		
SCA	BDI	0.017	0.058	(0.771)	2.134	1.10%
	Bloomberg	0.036	0.183	(0.843)		
	Forest	0.052	0.050	(0.299)		
	LME	0.274	0.160	(0.088)*		
SSAB	BDI	-0.027	0.075	(0.725)	2.326	13.66%
	Bloomberg	0.215	0.201	(0.285)		
	Forest	0.190	0.083	(0.024)**		
	LME	1.075	0.252	(0.000)***		

1. Significance levels: * = 10 %, ** = 5 %, *** = 1 %
2. DW = Durbin-Watson statistic

Appendix 6 – Out-of-sample prediction

Below is the result from the out-of-sample predictions presented. They are produced using a one period growth rate. For comparison the best in-sample predictions from every prediction are added in the table. NEG means that the value was negative and the underlined values are the best performed prediction on the predicted asset for that commodity. For Boliden the size of the window is 160 and 100.

		Expanding window		Rolling window		
Dependent V	Variable	200 Months	120 Months	200 Months	120 Months	Best in-sample
OMX	BDI	0.48%	0.85%	NEG	0.09%	0.50%
	Bloomberg	2.89%	2.16%	2.88%	1.17%	2.40%
	Forest	1.77%	0.97%	NEG	NEG	1.40%
	LME	12.59%	10.25%	11.94%	7.45%	12.30%
	SP	NEG	NEG	NEG	NEG	0.70%
Atlas Copco	BDI	NEG	NEG	NEG	NEG	NEG
	Bloomberg	5.06%	4.68%	4.95%	3.20%	4.68%
	Forest	2.70%	2.59%	2.47%	NEG	2.31%
	LME	5.88%	5.72%	1.98%	1.29%	5.49%
	SP	3.13%	2.76%	3.00%	1.11%	2.74%
Boliden	BDI	0.76%	NEG	NEG	NEG	1.13%
	Bloomberg	2.81%	0.30%	2.22%	NEG	2.38%
	Forest	7.13%	6.42%	7.27%	4.32%	7.31%
	LME	13.98%	10.24%	12.55%	11.12%	14.67%
	SP	2.62%	NEG	2.62%	0.99%	2.17%
Holmen	BDI	NEG	NEG	NEG	NEG	NEG
	Bloomberg	0.21%	NEG	NEG	NEG	NEG
	Forest	NEG	NEG	NEG	NEG	NEG
	LME	1.25%	0.31%	0.78%	NEG	0.86%

	SP	NEG	NEG	NEG	NEG	NEG
HM	BDI	NEG	NEG	NEG	NEG	NEG
	Bloomberg	0.11%	NEG	NEG	NEG	NEG
	Forest	0.29%	NEG	NEG	NEG	NEG
	LME	0.71%	NEG	NEG	NEG	0.35%
	SP	0.18%	NEG	NEG	NEG	NEG
Maersk	BDI	0.84%	NEG	NEG	NEG	1.18%
	Bloomberg	8.50%	8.42%	8.34%	8.10%	8.21%
	Forest	2.23%	1.63%	NEG	NEG	1.82%
	LME	5.68%	4.66%	3.78%	3.49%	5.30%
	SP	6.94%	6.59%	6.99%	6.72%	6.60%
Sandvik	BDI	NEG	NEG	NEG	NEG	NEG
	Bloomberg	5.98%	5.09%			5.60%
	Forest	1.01%	0.42%	NEG	0.02%	0.65%
	LME	6.41%	5.15%	6.18%	2.13%	6.04%
	SP	5.15%	4.20%	5.00%	2.87%	4.78%
SCA	BDI	NEG	NEG	NEG	NEG	NEG
	Bloomberg	1.11%	0.73%	NEG	NEG	0.84%
	Forest	0.43%	0.40%	NEG	NEG	0.08%
	LME	2.16%	2.15%	0.64%	NEG	1.88%
	SP	0.69%	NEG	0.40%	NEG	0.37%
SSAB	BDI	NEG	NEG	NEG	NEG	NEG
	Bloomberg	7.41%	5.69%	5.55%	5.71%	7.07%
	Forest	2.25%	1.80%	1.78%	1.04%	1.96%
	LME	13.14%	12.65%	9.42%	8.96%	12.82%
	SP	5.34%	3.06%	4.12%	0.48%	5.14%