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Predicting Stock Markets with Commodities

An Empirical Study on the Nordic Market

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Abstract

This study examines if commodity indices can be used to predict stock index returns on the Nordic financial markets. With a forecast period between 2000 and 2016, the study is conducted with an Ordinary Least Squares method to predict both in-sample and out-of-sample. The results indicate that the Baltic Dry Index and the London Metal Exchange Index are the best predictors of monthly stock returns for in-sample predictability. When testing for state-switching abilities of the commodity variables, we observe that predictability is only found in recessions and disappears in expansions. We also find evidence pointing in the direction of increasing commodity prices being better news in recessions than in expansions. Our estimates perform poorly out-of-sample, indicating that the information possessed by our predictions is of little use for an investor seeking profitable investment opportunities. The portfolios based on the significance of our estimators fail to outperform their respective benchmark index in 25 out of 28 cases.

Keywords: Commodities, stock returns, predictability, state-switching, trading strategy

Preface

This thesis was written during the spring semester of 2017, at the Department of Economics at Lund's University. The thesis is a final project to retrieve a Master of Science in Finance.

We want to take the opportunity to thank Hans Byström for his help throughout the process of the thesis.

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1 Introduction

In this thesis, we attempt to find in-sample and out-of-sample predictability of both nationwide and sector specific Nordic stock indices with the help of six different commodity indices. Additionally, we are, in the case of significant predictability, also using a portfolio strategy based on the estimations from our empirical research in an attempt to beat a buy-and-hold position in the given stock index. The study is conducted with a monthly, weekly and daily time horizon with an in-sample period between January 1st, 2000 and December 31st, 2011 and an out-of-sample period between January 1st, 2012 and December 31st, 2016.

Since the emergence of equity markets, investors have been interested in ways of predicting the movements of stock prices to earn higher returns than the market. An early example is Dow (1920), who tried to predict the equity market with dividend ratios. Recent research has established the certainty of stock market predictability in in-sample regression analysis and many predictors have been used for this purpose (Rapach et al., 2013; Lettau & Ludvigson, 2001; Fama & French, 1988). Historically in-sample predictions have been critiqued for performing poorly out-of-sample and thus being seemingly useless for the purpose of financial investors (Goyal & Welch, 2008; Dangl & Halling, 20112).

Nevertheless, the certainty of stock market predictability is still a widely debated subject, and scholars are constantly disagreeing on the validity of this theory. The opposite argument to stock market predictability was introduced already in 1863 when Regnault paved the way for the idea of stock prices following a random walk independent of previous stock prices (Le Galle & Jovanovic, 2001). During the 20th century the development of the random walk hypothesis continued and ended up in, perhaps to this day, the most widespread financial theory of all time, the Efficient Market Hypothesis by Fama in the 1960s (Fama, 1965). The Efficient Market Hypothesis states that stocks always trade at their fair value, meaning that all possible relevant information available to investors is reflected in the current stock price. This claim implies unpredictability in stock markets, but investors still look for ways to earn equity premiums above the benchmark, with the help of complex analysis tools, and many claim to have succeeded (Coval et al., 2005).

Even though both equity and commodity markets have existed for a long time, only a few studies have been conducted on the connection between the two (Black et al., 2014). The results of the existing research are nonetheless clear on the significant ability to predict stock markets with commodities, and further research needs to be done in the field to strengthen the connection. Some noteworthy research includes Jacobsen et al. (2016), who predicted stock markets with the help of industrial metals, Bakshi et al. (2011), who used the Baltic Dry Shipping Index and further, Black et al. (2014), who tried to predict the S&P 500 Index with the help of both individual commodities and broad commodity indices. Previous research will be presented in more depth later in this chapter.

To establish the connection between the price of commodities and stock prices we need to consider the dynamics of stock market prices. A stock is priced based on its expected future cash flows (Koller et al., 2015). An important value driver for the cash flow within a company is evidently their costs. Hence, it is not farfetched to state that many firms are heavily dependent on fluctuations of commodity prices. Airline companies are dependent on oil prices and mining companies on mineral and metal prices (Seibert, 2015; Team Wall Street Survivor, 2017). Taking this into consideration commodity prices are vital for firms as their costs can both increase and decrease due to commodity price fluctuations. This makes it compelling to study the stock price movements in reaction to commodity price movements. Do stock prices instantly reflect all new information arriving from the commodity markets or do arbitrage opportunities arise, disproving the Efficient Market Hypothesis?

Not only is it interesting to see if predictability exists between equity and commodity indices but also how this predictability changes over time. Notable research has proven that the predictive power of various economic factors over stock returns show a strong time-varying behavior (Pesaran & Timmerman, 1995; Dangle & Halling, 2012; Henkel et al., 2011; Boyd & Jagannathan, 2005). The predictability is strong in recessions but fades in expansions. Henkel et al. (2011) argue that this relationship stems from the counter-cyclicality of risk premiums and the fact that investors demand higher risk premiums in bad times when the volatility of stocks is higher. Synchronously, stock prices are more sensitive towards changing expectations in bad times and hence easier to predict. Regardless of the arguments for why the time-varying behavior exists, it is an interesting factor of stock return predictions and something that cannot be ignored when analyzing the predictability performance of commodity returns.

Besides being time-varying in the sense of predictability, Jacobsen et al. (2016) also found evidence stressing state-switching abilities for industrial metal returns. In their study the coefficient for the lagged industrial metals variable changed sign depending on the state of the business cycle, finding a negative relationship between stocks and commodities in expansions and a positive one in recessions. Consequently, the time-varying aspect of stock market predictions in relation to commodity prices is interesting for several reasons.

Our study draws upon previous research within the field with a few distinctive modifications. We focus on the Nordic stock market, an area not mentioned in previous studies. Not only are we predicting the stock market in Sweden, Denmark, Finland and Norway with the help of commodities, but we are also constructing a trading strategy based on our estimations in the case of statistically significant results. The portfolios are tested in the out-of-sample period trying to beat a buy-and-hold position on the corresponding indices, something that would challenge the Efficient Market Hypothesis. In contrast to previous research, which primarily focuses on predictability for monthly returns, we will also try to find significant estimations with a weekly and daily time horizon.

In the second and third chapter, the theory and statistical tests are discussed. Chapter four describes all data used in the study and gives a brief explanation of why each specific variable is used. The following chapter, chapter five, explains the procedure of the study. The purpose of the chapter is to give a clear view of the process of the study in such a way that it is possible for the reader to replicate the study and obtain the same results presented in chapter six. Chapter seven aims to give an analysis of the results. Chapter eight summarizes the thesis and proposes ideas for further studies.

1.1. Questions at Issue

The questions at issue for the research are:

- Can commodity index returns predict the Nordic stock markets?

- Does the predictability have time-varying properties depending on the state of the business cycle?

- If a predictability relationship is found, can a trading portfolio be constructed, based on the estimates, to create risk-adjusted excess return compared to the benchmark index?

1.2. Earlier Research

Jacobsen et al. (2016) are investigating the predictability of monthly industrial metal returns on both the U.S. market and on equity markets of other industrialized countries. They use a state-switching model trying to find business cycle specific results based on two states; recession and expansion. Their results show a strong ability of industrial metals to predict stock markets, with monthly out-of-sample R^2's of 3% to 8%. Interestingly, the coefficients for the lagged industrial return variable is significant in both states and switches sign from negative in expansions, to positive in recessions, a feature unique for industrial returns according to the researchers. Further, the authors state that these state-switching abilities stem from the fact that increasing metal prices indicate an overheated economy and inflation in expansions, and are a leading indicator of increasing overall demand in recessions. Other commodity indices are also tested for predictability in the study, but they are all found to be inferior estimators of stock returns in comparison to industrial metals.

Instead of using industrial metals Bakshi et al. (2011) predict stock markets with the Baltic Dry Shipping Index (BDI). The BDI is widely recognized as a "leading indicator of economic activity reflecting global demand for raw materials". Their findings show that BDI has a predictive ability for both in-sample tests and out-of-sample statistics. The significant predictability of the BDI holds not only for stock market returns but for other commodity index returns and growth in the real economic activity across a range of developed and emerging economies. Further, the authors state that the BDI performs better than other, more conventional estimators when it comes to stock return prediction.

When investigating the long-run relationship between the S&P 500 Composite Index and the S&P GSCI Total Return Index, which is an index covering the whole commodity market, Black et al. (2014) find that the connection changes over time with several structural breaks. The most noticeable break being the dot.com bubble, where they argue for a strengthening relationship after the bubble, derived from the financialization of commodities. The financialization is a concept introduced during the dot.com crisis when commodity weights in portfolios increased substantially as both equity and bond yields were low. The paper

emphasizes the time-varying relationship between stock and commodity returns and recommends a forecast model that allows for changes in the parameter values within the framework of the forecast regression.

Many estimators have been suggested by the academic literature to be good predictors of the equity premiums. Goyal and Welch (2008) are, in their paper, analyzing both the in-sample and out-of-sample predictability for a handful of these estimators, such as corporate dividend yields and earnings ratios, the Consumer Price Index and the long-government bond yield. They conclude that these models would not have provided investors with any useful information as they performed poorly both in-sample and out-of-sample. These results strongly contradict much of the previous research done in the field of stock return predictability.

1.3. Limitation

In relevance to the authors, the equity indices used are limited to the Nordic countries Sweden, Norway, Finland, and Denmark. Iceland was not included in the research due to lack of data. The selections of commodity indices were primarily based on their contribution to previous research but also upon their specific commodity weights and liquidity on the financial market. In addition to testing predictability of the broad country specific indices we also selected a few sector specific indices. These were handpicked based on their potential high dependency upon commodity prices. Data for the sector specific indices are limited to the years from 2000 to 2016 due to lack of data before this period. Additional indices could have been included in the thesis, but for the data to be manageable, the study is limited to six commodity indices and 13 equity indices. Finally, the data was collected on a daily, weekly and monthly basis.

As the thesis is written in Sweden, it holds a Swedish investor's perspective, meaning that a one month Swedish Treasury bill will be used as the risk-free asset when estimating Sharpe ratios for our equity portfolios.

2 Theory – Efficient Market Hypothesis

2.1. The Efficient Market Hypothesis

The Efficient Market Hypothesis is arguably the most well-known and controversial out of all finance theories and has been so since the 1960s. The Efficient Market Hypothesis was first developed by Fama (1965) and states that stock prices always trade at their fair value, which means that all possible relevant information are available to investors and incorporated in the stock price. When new information gets official, market participants react quickly, and the stock price moves to a new market equilibrium. Hence, predicting the market using complex analyzing tools such as fundamental or technical analysis cannot render higher return than the market as a whole, except by chance. According to the Efficient Market Hypothesis, stock price movements are stochastic and follow a random walk, independent of previous stock prices (Fama, 1965).

The key reason for the existence of efficient markets is, according to Clarke et al. (2001), the extreme competition on financial markets. The likelihood of finding mispriced securities gets smaller and smaller as more financial analysts try to exploit arbitrage opportunities and consequently increase competition. This should mean that markets are getting more efficient by the minute as competition is constantly growing. Thus, the number of investors beating the market with the help of superior information techniques will be smaller, and analysts who are acting on the information will not be able to earn any abnormal returns after adjustment for transaction costs (Clarke et al., 2001).

2.1.1. Critics

Despite severe enhancements in the quality and quantity of data, the ability to process data and improvements of both statistical analysis and theoretical modeling, there is still little unity among economists as to the legitimacy of the model (Sewell, 2012). Many investors claim to have found analytical models serving as tools to "beat the market", something that would be impossible on an efficient market where stock prices follow a random walk (De Bondt & Thaler, 1984; Coval et al., 2005; Lynch, 1989; Lee & Swaminathan, 2000). Proof of these investors being successful on financial markets for long periods of time would be a clear violation of the Efficient Market Hypothesis and a strong argument for the presence of arbitrage opportunities on financial markets.

In an efficient market, all stocks are perfectly priced, and there is no need for market participants to invest actively, paying substantial sums in transaction and administrative costs. Under- and overvalued stocks are impossible to find, suggesting that holding a long position in a fully diversified stock portfolio is the perfect stock market strategy. This is not the behavior we observe on the stock markets, and since a common assumption in finance theory is that market participants are rational, this is a clear contradiction (Chavas, 1999). People are actively trading despite the Efficient Market Hypothesis stating they should keep a market index to maximize their expected value while simultaneously decreasing risk.

Violations of the Efficient Market Hypothesis are in general hard to prove, but several researchers have found clear evidence in the direction of violations of the strongest form of efficiency (Rozeff & Zaman, 1988; Ahern, 2015). In the strongest form of efficient markets, not even insiders can earn abnormal returns on their information advantage. Rozeff and Zaman (1988) go so far as to state that even outsiders mimicking the trades of insiders could earn abnormal returns, a statement heavily disrupting the idea of efficient markets.

2.1.2. Support

Several studies have been investigating the performance of fund managers' portfolios in relation to the benchmark index. They tend to end up with the same conclusion: professional investors do not beat the benchmark index on average when comprising their higher than average transaction costs (Malkiel, 2005). This means that one is, on average, better off investing in a low-cost index fund than in one of the costly, actively traded, investment funds.

A natural question is; how come some investors have been able to beat the market consecutively for long periods of time? One reason for this, which is often stated by efficient market advocates, is that the presence of these investors is a happenstance and the consequence of pure luck (Clarke et al., 2011). With the large number of investors active on current financial markets, there is no wonder that some of these have performed outstandingly well over long periods even without superior analytical tools.

3 Theory – Statistical Issues and Tests

3.1. Stationarity

A strictly stationary time series process has a distribution that remains the same as time progresses, keeping a constant mean, constant variance and constant autocovariance. There exist two main forms of non-stationarity processes. In a stochastic non-stationarity time series, the process determining the evolution of a variable is in itself non-stationary, leading to shocks having a permanent effect on the process causing it to lose its mean-reverting abilities. A trend-stationary process has a non-constant mean because it follows a deterministic trend over time but is stationary around this time trend. The use of non-stationary time series can lead to spurious regressions, causing inflated R^2-values and incorrect significance. When conducting standard regression on non-stationary data, the standard assumptions for asymptotic analysis will also be violated, meaning that the series will not follow the distribution intended. (Brooks, 2014)

To test for stationarity, one can conduct an Augmented Dickey-Fuller test which can test for both stochastic non-stationarity and trend-stationarity. The null hypothesis states that the time series is non-stationary. (Brooks, 2014)

3.2. Multicollinearity

The problem of multicollinearity occurs when two or more of the variables in a regression model are correlated to a high degree. This causes the regression to get an inflated R^2-value as well as high standard errors, making the estimations insignificant. When two variables are highly correlated it becomes hard to observe the individual contribution of each variable to the overall fit of the regression. Another problem which arises is that the regression becomes sensitive when adding or removing variables. Thirdly, the significance tests might give inappropriate conclusions due to wide confidence intervals. One of the mentioned solutions, when the variables suffer from multicollinearity, is to drop one of the correlated variables from the regression. (Brooks, 2014)

Multicollinearity can be tested by studying a correlation matrix between the variables in question. To decide whether multicollinearity poses a problem for the regression, the rule of thumb of over 80% correlation between the variables can be used. (Brooks, 2014)

3.3. The Adjusted Coefficient of Determination, Adjusted R^2

The regular R^2-value is a relevant value when performing OLS regressions. The value describes to what extent the predictor, the explanatory variables x_i, explain the change in the dependent variable, y_i. If $R^2 = 1$, the variables included in the regression account for all of the variation in y_i perfectly, and if $R^2 = 0$ the variables are of no use for explaining the dependent variable. (The Pennsylvania State University, 2017).

The adjusted R^2 serves the same purpose as R^2, but it adjusts for the number of independent variables in the model, that is, it penalizes models using independent variables that do not fit the model.

3.4. Autocorrelation

If the residuals in a regression are dependent on each other, the regression suffers from autocorrelation. Regression analysis performed on time-series often show signs of autocorrelation which poses a big problem in the inference of the regression results. Standard errors are miscalculated, and R^2-values get inflated. One of the reasons for autocorrelated regressions arises when the dependent variables are dependent on their past values, making the model an autoregressive process. By examining the dependent variables with traditional correlogram analysis, you can detect potential autocorrelation in the time series. (Brooks, 2014)

A possible remedy for autocorrelation stemming from autocorrelated dependent variables is to include lagged regressands as independent variables in the model. If the model suffers from autocorrelation for other reasons, Newey-West standard errors can be used in the model to ensure rightful inference of the results and elimination of the problem with inflated R^2-values. A Breusch-Godfrey test can be used to detect possible autocorrelation in a regression. (Brooks, 2014).

3.5. Sharpe Ratio

The Sharpe ratio is a ratio for the risk-adjusted return. The ratio is defined by the expected return, $E(r_i)$, reduced by the risk-free return, r_f, in relation to the asset's risk, measured by the standard deviation, $\sigma(r_i)$. The ratio can be interpreted as the average excess return an investor earns per unit of volatility. A negative Sharpe ratio indicates that the risk-free investment is a better choice than the asset in question. Contrary, a positive Sharpe ratio indicates that the asset is a better investment than the risk-free asset, considering the return in relation to the risk. (Sharpe, 1966)

$$r_i = \frac{E(r_i) - r_f}{\sigma(r_i)} \tag{1}$$

Since the expected return is unknown, the estimated Sharpe ratio is used instead. The estimated Sharpe ratio is calculated with ex-post data, where m_i is the average excess return, r_{it}, subtracted by the risk-free investment, rf_t, and s_i is the standard deviation for asset i:s return (Jobson & Korkie, 1981).

$$\widehat{sr_i} = \frac{m_i}{s_i} \tag{2}$$

$$m_i = \frac{1}{T}\sum_{t=1}^{T} d_{it} \tag{3}$$

$$s_i = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(d_{it} - m_i)^2} \tag{4}$$

$$d_{it} = (r_{it} - rf_t) \tag{5}$$

3.5.1. Tests on Sharpe Ratio

Jobson & Korkie (1981) developed a method to show a significant difference between Sharpe ratios for different assets. One can use the method both with a two-sided or one-sided alternative hypothesis. To differentiate if one Sharpe ratio is greater than the other the following null and alternative hypothesis are examined:

$$H_0: sr_{ij} \equiv sr_i - sr_j = \frac{m_i}{s_i} - \frac{m_j}{s_j} = 0$$

$$H_1: sr_{ij} > 0$$

The transformed difference for the Sharpe measure is written as follows:

$$\widehat{sr}_{ij} \equiv \widehat{sr}_i - \widehat{sr}_j = s_j m_i - s_i m_j \tag{6}$$

The asymptotic distribution of the transformed difference is normally distributed with the mean sr_{ij} and variance θ.

$$\theta = \frac{1}{T}\left[2s_i^2 s_j^2 - 2s_i s_j s_{ij} + \frac{1}{2}m_i^2 s_j^2 + \frac{1}{2}m_j^2 s_i^2 - \frac{m_i m_j}{2s_i s_j}\left[s_{ij}^2 + s_i^2 s_j^2\right]\right] \tag{7}$$

where s_{ij} is the estimated covariance between the excess returns for asset i and j (Jobson & Korkie, 1981). The test statistic is calculated as follows:

$$z(sr_{ij}) = \frac{\widehat{sr}_{ij}}{\sqrt{\theta}} \sim N(0,1) \tag{8}$$

4 Data

4.1. Data Collection

Following Jacobsen et al. (2016), we use commodity indices on futures contracts instead of spot prices because they are more liquid. According to The Economic Times (2017), a future contract is "a contract between two parties where both parties agree to buy and sell a particular asset of specific quantity and at a predetermined price, at a specified date in the future". Literature suggests that commodity futures' prices follow spot prices (Sockin & Xiong, 2015).

Historical price data from January 1st, 2000 to December 31st, 2016 is collected for six commodity indices, 13 equity indices and three control variables within the four Nordic countries Sweden, Denmark, Norway, and Finland. Two more variables are collected; the one month Swedish Treasury bill and the Chicago Fed National Activity Index (CFNAI). A full list of each index used for the paper as well as the platform used to retrieve the data is found in Table A 1 and Table A 2 in the Appendix.

Data was collected on a daily, weekly and monthly basis for the period. This enables three studies for the relationship between commodities and equity indices. Earlier studies have not included daily nor weekly data. We choose to include data on a daily and weekly basis due to our belief that, if a relationship between the two markets exists, the equity market should react sooner rather than later once new information about the commodity market is released.

4.2. Independent Variables - Commodity Indices

Following previous research, we use several commodity indices for prediction of stock markets in this research paper. Commodity indices are used instead of single commodities as the latter is highly volatile and affected by idiosyncratic events (Black et al., 2014).

Bloomberg Commodity Index

The Bloomberg Commodity Index (Bloomberg) is a well-diversified commodity index which includes energy, grains, livestock, softs, industrial metals and precious metals commodities. The index tracks prices of futures contracts on physical commodities. No commodity can be

weighted less than 2% or more than 15%, and no single sector can be weighted over 33% of the index portfolio (Bloomberg, 2015).

S&P GSCI Commodity Index

Following Black et al. (2014), we use S&P GSCI Commodity Index (S&P) as an estimator of stock returns in our study. Similar to Bloomberg, the S&P is an index that is well diversified over all different commodity types. The difference between the two is that S&P has a greater exposure to the energy sector. As of today, the index comprises 24 commodities from all commodity sectors; energy, industrial metals, precious metals, agriculture, and livestock (Pimco, 2016). The index bases its weight upon trading volume in the underlying assets. It is considered a benchmark for investment performance in the commodity markets (Trade Commodities, 2017).

Baltic Dry Index

The Baltic Dry Index (BDI) measures shipping costs for dry bulk commodities that are traded on the London-based Baltic Exchange (Odom, 2010). The index is a good indicator of the demand and supply of different commodities. Bakshi et al. (2011) argue that BDI is a leading indicator of economic activity and hence a good predictor of stock market returns.

LMEX Index

The London Metal Exchange Index (LMEX) comprises the six primary non-ferrous metals; Aluminum, Copper, Lead, Nickel, Tin and Zinc. The highest weighting is given to Aluminum and Copper, based on global production volume and trade liquidity (LME, 2017). Jacobsen et al. (2016) show that industrial metals predict stock market prices for both the U.S. market as well as for international markets.

S&P GSCI Energy Index

The S&P GSCI Energy Index (Energy) is exposed to the energy sector reflecting the returns of six energy commodities; West Texas Intermediate light sweet crude oil, Brent crude oil, gas oil, heating oil, RBOB gasoline and natural gas (ETC Securities, 2017). Oil and gases are some of the most traded commodities in the world (Kowalski, 2017), and thus a highly interesting sector to include in the study.

Random Length Lumber Index

The Random Length Lumber Index (Lumber) provides the future price of a standard lumber dimension (CME Group Inc., 2009). According to Skogsindustrierna (2016), the forest industry accounted for approximately 11% of Sweden's exports in 2016, and therefore this index is an interesting commodity for the study.

4.3. Dependent Variables - Equity Indices

Several equity indices are used for the study. We choose to include equity indices from the Nordic markets. Equal to Black et al. (2014), we include large equity indices in our paper. Black et al. (2014) used the S&P 500 Composite Index for the US market, but instead, we use the equivalent indices for Sweden, Norway, Denmark, and Finland. Additionally, unlike earlier studies, sector indices in each specific country are included to test for more specific commodity and equity relationships. The argument for including such stock indices is that we believe that some sectors are more exposed to fluctuations in certain commodities than others. The same sector specific indices are found for three out of the four countries. The sector-specific indices do not exist for the Norwegian stock market which leads us to only have one index for Norway, the All Share Index. Different to Iceland, Norway is still included in the study due to its large exposure to oil and metal commodities as this sector constitutes 22% of the country's GDP (European Commission, 2017). All sector specific indices are chosen based on how exposed the companies comprised in the indices are to commodities. The indices are described below.

OMX Stockholm GI Index (Sweden All Share)

The index represents all stocks on the Swedish equity market. Dividends are re-invested in the index (Nasdaq OMX, 2017).

OMX Copenhagen GI Index (Denmark All Share)

The index represents all stocks on the Danish equity market. Dividends are re-invested in the index (Nasdaq OMX, 2017).

OMX Helsinki GI Index (Finland All Share)

The index represents all stocks listed on the Helsinki Stock Exchange. Dividends are re-invested in the index (Nasdaq OMX, 2017).

Oslo Børs All Share Index (Norway All Share)

The index represents all stocks listed on the Oslo Børs. Dividends are re-invested in the index (Oslo Børs, 2017).

Basic Materials

Companies found in a general Basic Materials Index operate with extraction and primary refinement of raw materials. Materials such as chemicals, metals, nonmetallic and construction materials, forest, wood and paper products, and container and packaging products are all classified as raw materials (The New York Times, 2017). As commodity indices such as Bloomberg and S&P are heavily weighted towards these types of materials, it would be of interest to include the Basic Materials Index.

Industrials

Industrial indices consist of companies with operation providing industrial and commercial supplies and services, distribution operations and transportation services. The companies included might operate within aerospace, lumber production, construction, metal fabrication or industrial machinery (The New York Times, 2017). Consequently, these companies are dependent on prices of commodities such as metals, lumber, energy and fuels.

Consumer Goods

What defines Consumer Goods companies is that they sell final products to individual consumers (Ycharts, 2017). As the sector is broad, covering companies operating in everything from food production to automobiles, it is a good sector to include in the study.

Finally, it would have been of interest to include an index for Oil and Gas as some of the commodity indices include these commodities and because Crude Oil is the most traded commodity in the world (Kowalski, 2017). Unfortunately, the data for the country-specific data on the index OMX Oil & Gas does not match the historical length needed when performing the study.

4.4. Control Variables

Control variables are included in the study to strengthen the validity of the estimations, making the results more robust. Trying to predict equity premiums, Goyal and Welch (2008)

include several variables in their study that are widely accepted to predict excess returns. Two of these are the 10-year government bond rate (Bond) and the Consumer Price Index (CPI). We use these two variables as control variables.

Further, Rapach et al. (2013) proved that the S&P 500 Composite Index serves as a predictor for non-U.S. industrialized countries. This index is likewise included in this paper as a control variable.

Due to lack of data for the consumer price indices they can only be used as a control variable for monthly data. For the same reason, bond rates for the countries can only be used for monthly and weekly data.

4.5. State-Switching Variable - CFNAI

The Chicago Fed National Activity Index (CFNAI) is a monthly index designed to gauge the overall economic activity in the U.S. and is constructed by researchers at the Federal Reserve Bank of Chicago. The index is a weighted average of 85 monthly indicators of national economic activity and serves as an estimator of the current level of economic activity. The average value of the index is zero, and its standard deviation is one, were a value below $-0{,}7$ is signaling a recession. It is released once every month on scheduled days, usually towards the end of the month. Two periods are forecasted as recessions by the CFNAI. These periods stretch from January 2000 to January 2001 and December 2007 to August 2009. (Federal Reserve Bank of Chicago, 2016)

The best for the precision of our forecast would undoubtedly be to have an index for the current level of economic activity for the Nordic countries. No such index could be found, and thus, we are limited to the use of the numbers from the CFNAI. This might not be completely accurate since there are differences in the state of the business cycle in the U.S. and the Nordics, but research points in the direction of a high convergence between the two. Artis and Zhang (1999) interestingly present research to show that the business cycles of the Nordic countries converge more to the U.S. business cycle than to business cycles of countries such as Germany and other large economies in Europe. Research has also indicated that the industrialized countries have become more and more synchronized as international trade has

increased which further develops the link between the business cycles of all industrialized countries (Kose et al., 2003; Inklaar et al., 2008; Calderón et al., 2007).

Unfortunately, the CFNAI is released with a lag of one month which makes it imperfect for investors needing data for the current business cycle level. Our state-switching model is hence primarily used in our in-sample period to investigate whether we observe time-varying patterns of predictability for commodities in different times of the business cycle. For the purpose of operating as a variable for the current state of the business cycle in our portfolio strategy, it is still the best possible estimator, which convinced us to use it.

4.6. Risk-Free Asset – One Month Swedish Treasury Bill

The paper is written from a Swedish investor's perspective. Therefore, a one month Swedish Treasury bill is used when constructing the Sharpe ratio for the portfolios created, during the time frame January 1st, 2012 to December 31st, 2016. As no Swedish Treasury bills are offered for a shorter term than one month, the data is transformed to weekly and daily returns.

5 Methodology

5.1. Data Transformation

All variables are transformed into log returns to smoothen the return series and to ensure statistically desirable properties. The logarithmic return for the indices is calculated through the following formula (Tsay, 2002):

$$logreturn_t = ln(price_t) - ln(price_{t-1}) \tag{9}$$

All log return series are tested for stationarity, and independent variables are tested for multicollinearity. The dependent variables are also tested for autocorrelation via correlogram analysis.

5.2. Model

In this section, we will present our models for in-sample predictability in the period 1st of January 2000 to 31st of December 2011. In line with previous research, all our stock index return predictions are conducted with an Ordinary Least Squares method (Jacobsen et al., 2016; Bakshi et al., 2011; Goyal & Welch, 2008). Lagged dependent variables are added to the regressions to minimize potential autocorrelation problems. To test for autocorrelation, Breusch-Godfrey tests are conducted and in the few cases where autocorrelation is found we follow the procedure from previous research and use Newey-West standard errors to ensure correct inference of the results and eliminate the possibility of inflated R^2-values (Bakshi et al., 2011; Jacobsen et al., 2016). The significance level is set to 5% for all tests and regressions in the thesis. Estimations receiving *p*-values above this threshold are regarded as insignificant.

5.2.1 Univariate Model

As a start, all our six commodity indices are tested individually on each equity index, for our three time horizons, using a univariate regression model for the in-sample period January 1st, 2000 to December 31st, 2011. This is done to get an indication of the prediction power of the commodity indices without the presence of control variables (Jacobsen et al., 2016).

$$Equity\ index\ return_t = \alpha + \beta_i Commodity\ index\ return_{i,t-1} + \varepsilon_t \quad (10)$$

To further investigate the robustness of our initial predictions, financial control variables are added to the regressions that indicate statistically significant results on the 5% level. To solve the fact that the dependent variables show signs of the first-order autocorrelation, a lagged dependent variable is also added to the regression, making it an autoregressive model with one lag. Newey-West standard errors are used in the cases where the regression shows signs of autocorrelation to prevent wrongfully estimated standard errors and inflated R^2-values (Jacobsen et al., 2016). The equation used looks as follows:

$$Equity\ index\ return_{i,t} = \alpha + \beta_i Commodity\ index\ return_{i,t-1} + \sum_{i=1}^{n} \omega_i Control\ variable_{i,t-1} + \mu_i Equity\ index\ return_{i,t-1} + \varepsilon_t \quad (11)$$

We add three control variables to check the robustness of the results; CPI, government bonds and S&P 500. Due to lack of data, CPI is only available for monthly returns, and the government bond variables are only available for the monthly and weekly time horizon. Concluded by previous research, using only one control variable in models for stock return prediction is satisfactory (Jacobsen et al., 2016).

5.2.2. State-Switching Model

The basic state-switching model is conducted for the in-sample period in the following fashion:

$$Equity\ index\ return_{i,t} = \alpha + \beta_i Commodity\ index\ return_{i,t-1} Recession_{t-1} + \beta_i Commodity\ index\ return_{i,t-1} Expansion_{t-1} + \varepsilon_t \quad (12)$$

With the state-switching model, we investigate whether commodity index returns display time-varying predictability patterns. In line with previous research, we use two states, recession and expansion (Jacobsen et al., 2016). The added dummy variables $Recession_{t-1}$ and $Expansion_{t-1}$ capture the current state of the business cycle based on estimations of the CFNAI. $Recession_{t-1}$ is a dummy variable that takes on the value 1 when the economy is contracting, and the value zero if the economy is expanding. $Expansion_{t-1}$ is a dummy variable that takes on the value 1 when the economy is expanding, and the value zero when it

is contracting. If at least one of the two beta values is significant at the 5% level the model is also tested with control variables to ensure robust results:

$$Equity\ index\ return_t = \alpha + \beta_i Commodity\ index\ return_{i,t-1} Recession_{t-1} + \beta_i Commodity\ index\ return_{i,t-1} Expansion_{t-1} + \sum_{i=1}^{n} \omega_i Control\ variable_{i,t-1} + \mu_i Equity\ index\ return_{i,t-1} + \varepsilon_t \quad (13)$$

5.3. Out-of-Sample Predictability

To measure the quality of our estimations out-of-sample, we calculate an out-of-sample R^2 value (R^2_{OOS}), a method applied by many previous studies (Jacobsen et al., 2016; Black et al., 2014; Goyal & Welch, 2008; Campbell & Thompson, 2007). The R^2_{OOS} is calculated via the following model:

$$R^2_{OOS} = 1 - \frac{MSE_{Prediction}}{MSE_{Actual}} = 1 - \frac{\sum_{t=1}^{T}(r_t - \hat{r}_t)^2}{\sum_{t=1}^{T}(r_t - \bar{r}_t)^2} \quad (14)$$

where $\hat{r}_t$ are the fitted values from the predictive regression, $\bar{r}_t$ is the average historical return from the in-sample period, and r_t is the actual returns in the out-of-sample period. Hence, a positive R^2_{OOS} indicates a lower mean-squared error from the predictive regression, relative to the mean-squared error based on the historical average return. A negative R^2_{OOS} would mean that our stock index return predictions are on average a worse prediction than the historical average.

The R^2_{OOS}'s are calculated to ensure the robustness of our in-sample predictions in an out-of-sample setting. All estimators that show statistically significant predictability in the presence of control variables in-sample are also tested out-of-sample. This is a necessity to ensure that the estimations from the in-sample prediction are useful for investors trying to find investment opportunities out-of-sample. To isolate the predictability of our commodity indices the R^2_{OOS}'s are calculated for the regressions without control variables. Previous research indicates that in-sample predictions perform poorly out-of-sample. This is something we explore further by creating R^2_{OOS}-values.

5.4. Trading Portfolio

The trading strategy is a new strategy tested by the authors, based on the significance found in our regressions. The portfolios are tested in our out-of-sample period between January 1st, 2012 and December 31st, 2016. The portfolios are updated at the end of every day, week or month depending on which time horizon used.

As discussed earlier in the paper, when variables included in a regression are highly correlated the problem of multicollinearity emerges. When the problem arises, there are some actions which can be used to eliminate the problem, one of them being to exclude one of the variables that are highly correlated. This action is used when creating the regressions for the trading strategy.

5.4.2. Creation of the Portfolios

The portfolios are created based on the significance found in earlier regressions. Portfolios are created both with and without state-switching variables. The commodity indices that were significant in the presence of control variables will be used to construct the portfolios. Since we are interested in the prediction power of the commodity indices alone, we will base our portfolios on estimations from regressions without control variables. When several commodity indices can explain the same stock index in the univariate regressions, they are tested jointly in the portfolio strategy. The portfolios are based on estimates from the following models:

$$Equity\ index\ return_t = \alpha + \sum_{i=1}^{n} \beta_i Commodity\ index\ return_{i,t-1} + \varepsilon_t \qquad (15)$$

$$Equity\ index\ return_t = \alpha + \sum_{i=1}^{n} \beta_i Commodity\ index\ return_{i,t-1} Recession_{t-1} + \sum_{i=1}^{n} \beta_i Commodity\ index\ return_{i,t-1} Expansion_{t-1} + \varepsilon_t \qquad (16)$$

If the fitted value for our dependent variable in period *t* is positive, we take a long position in the index in question, and if it is negative, we take a short position. Our positions are reevaluated at each new period depending on the fitted values. Four scenarios can incur:

- If a long position is acquired in the earlier period, and the prediction for the future period is an upturn, the position will be held without any change.

- If a long position is acquired in the earlier period, and the prediction for the future period is a downturn, the position will be sold, and a short position will be taken for the upcoming period.

- If a short position is acquired in the earlier period, and the prediction for the future period is a downturn, the position will be held without any change.

- If a short position is acquired in the earlier period, and the prediction for the future period is an upturn, the position will be sold, and a long position will be taken for the upcoming period.

5.4.3. Performance Comparison of Portfolios

To evaluate the performance of our portfolio compared to a buy-and-hold position in the same index, Sharpe ratios are constructed. To calculate the Sharpe ratios for the out-of-sample period equation 2 is used. As the thesis is written from the perspective of a Swedish investor, the one month Swedish Treasury bill is used as a measure of a risk-free investment.

To examine whether there is a significant difference between the Sharpe ratios of our own portfolios and the buy-and-hold portfolios, we follow Jobson & Korkie's (1981) method of performance comparison. For the purpose of studying if the Sharpe ratio with the higher value is statistically greater than its counterpart, we use the one-sided alternative hypothesis test from equation 6. If the null hypothesis cannot be rejected, the Sharpe ratio cannot be said to have a statistically higher value.

6 Results

6.1. Stationarity Test

The Augmented Dickey-Fuller tests for non-stationarity in time-series are rejected for all variables and time horizons both for trend-stationarity and stochastic non-stationarity. The possibility of spurious regressions stemming from non-stationary time-series can be dismissed. The results from the stationarity tests can be found in the appendix in Table A 3, Table A 4 and Table A 5.

6.2. Multicollinearity

When studying the correlation matrices, we find near multicollinearity (>80%) between Bloomberg and Energy, Bloomberg and S&P, and S&P and Energy for all time horizons. As S&P and Bloomberg are both well diversified and broad commodity indices, it is quite intuitive that they are highly correlated. S&P is an index weighted towards the energy commodity sector, hence the high correlation between Energy and S&P falls naturally. Furthermore, all country specific bond variables for our weekly data are correlated to a degree of 97% or higher. None of the bond variables are ever used in the same regressions as they are country-specific variables. The correlation matrices for the independent variables can be studied in Tables A 6, A 7 and A 8.

6.3. Univariate Regression

P-values and adjusted R^2-values are collected for 234 regression (six commodity indices * 13 equity indices * three time periods). The only two commodity indices to show statistically significant results in the presence of control variables for our monthly data are LMEX and BDI. Both LMEX and BDI proved to be significant on five out of 13 indices. The results from the regressions including control variables can be found in Table A 9 in the Appendix. When studying the commodity indices that pass the robustness tests in a setting without control variables, the adjusted R^2's for LMEX range from 2% to 8% and from 3% to 6% for BDI, which can be observed in Table 1. No pattern can be found based on the ability to predict any certain country or sector.

Table 1 – Univariate model: Monthly data, Jan 2000 – Dec 2011, 142 observations

Dependent Variable	Explanatory Variable	P-value	Coefficient	Adj R2
Denmark All Share	LMEX	0,000	0,232	8%
Denmark All Share	BDI	0,016	0,051	3%
Denmark Consumer Goods	BDI	0,002	0,085	6%
Finland All Share	LMEX	0,047	0,202	2%
Finland Industrials	LMEX	0,000	0,300	8%
Norway All Share	BDI	0,012	0,066	4%
Sweden All Share	BDI	0,021	0,055	3%
Sweden Basic Materials	LMEX	0,004	0,254	5%
Sweden Industrials	LMEX	0,006	0,231	5%
Sweden Industrials	BDI	0,026	0,059	3%

For the univariate regressions on the weekly time horizon, only four regressions pass the robustness check of control variables. The only two indices to show significance are Energy and S&P, which are both significant for the Sweden Consumer Goods Index and the Sweden Industry Index. The results from the regressions are presented in Table A 10 in the Appendix. Without the presence of control variables, the adjusted R^2's range from 0,7% to 0,9% for the Energy Index and the S&P Index can explain 0,7% of the future returns in the dependent variable for both equity indices. The results are found in Table A 14 in the Appendix.

No robust predictability can be found on the daily time horizon for our univariate regressions without state-switching abilities.

6.4. State-Switching Regressions

As for the univariate regressions with monthly time horizon, our dependent variables in the state-switching regressions are best explained by the LMEX and BDI indices. Interestingly, we are only able to find predictability in recessions. Significance in expansions cannot be found in any of the regressions. When including control variables for robustness our LMEX recession coefficient stays significant for all 13 stock indices, as can be seen in Table A 11 in the Appendix. The BDI recession coefficient is significant for seven indices, and both the Bloomberg and the S&P recession estimates stay significant for one index, the Finland Consumer Goods Index. Another difference between the coefficients for the two states is their values. In the regressions for the commodity indices that pass the robustness test in a setting without control variables, we can observe that the coefficient for the recession state is always positive and higher than the coefficient for the expansion state. As observed in Table 2, nine out of 22 regressions have a negative expansion coefficient. Five of those cases are observed

for the BDI variable, three for the LMEX variable and the last one for Bloomberg. Bear in mind that none of the expansion coefficients are significant on a 5% level. The adjusted R^2's for the same regressions range from 4% to 18% for the LMEX variable, from 4% to 17% for the BDI variable, 8% for Bloomberg and 7% for the S&P variable.

Table 2 – State-switching model: Monthly data, Jan 2000 – Dec 2011, 142 observations

Dependent Variable	Explanatory Variable	Rec P-value	Rec Coefficient	Exp P-value	Exp Coefficient	Adj R-squared
Denmark All Share	LMEX	0,000	0,492	0,678	0,034	15%
Denmark All Share	BDI	0,001	0,091	0,906	-0,004	6%
Denmark Basic Materials	LMEX	0,003	0,481	0,533	0,087	5%
Denmark Basic Materials	BDI	0,001	0,142	0,413	-0,041	6%
Denmark Consumer Goods	LMEX	0,000	0,693	0,450	0,080	18%
Denmark Consumer Goods	BDI	0,000	0,183	0,227	-0,047	17%
Denmark Industrials	LMEX	0,000	0,585	0,986	0,002	11%
Denmark Industrials	BDI	0,005	0,110	0,868	-0,007	4%
Finland All Share	LMEX	0,007	0,419	0,782	0,037	4%
Finland Basic Materials	LMEX	0,003	0,473	0,853	0,026	5%
Finland Consumer Goods	LMEX	0,000	0,593	0,613	-0,048	17%
Finland Consumer Goods	S&P	0,000	0,393	0,974	0,003	8%
Finland Consumer Goods	Bloomberg	0,001	0,484	0,574	-0,078	7%
Finland Industrials	LMEX	0,000	0,581	0,413	0,085	14%
Norway All Share	LMEX	0,000	0,462	0,688	0,043	8%
Norway All Share	BDI	0,000	0,138	0,407	-0,032	10%
Sweden All Share	BDI	0,010	0,081	0,595	0,019	4%
Sweden All Share	LMEX	0,002	0,358	0,867	0,016	6%
Sweden Basic Materials	LMEX	0,000	0,496	0,549	0,069	8%
Sweden Basic Materials	BDI	0,009	0,098	0,783	-0,012	4%
Sweden Consumer Goods	LMEX	0,005	0,302	0,980	-0,002	4%
Sweden Industrials	LMEX	0,001	0,444	0,532	0,068	7%

The recession coefficient is significant in the presence of control variables in four of our regressions with a weekly time horizon. Twice for the BDI Index, once for the LMEX Index and once for the Lumber Index. The expansion coefficient is never significant as can be observed in Table A 12 in the Appendix. As shown in Table A 15, the adjusted R^2's for the regressions of these indices in a context without control variables range from 1,4% to 1,8%.

For the regressions with the daily time horizon in the presence of control variables, the expansion coefficient is significant eight times and the recession coefficient only once. Four of the expansion coefficients are significant for the Sweden Basic Material Index and four for the Norway All Share Index. The adjusted R^2's in the regressions without control variables for the variables passing the robustness test range from 0,1% to 0,4% for the Sweden Basic Materials Index and from 0,2% to 0,7% for the Norway All Share Index. The recession estimate for BDI passes the robustness test for the Denmark Consumer Goods Index and the

adjusted R^2 for the given index without control variables is 0,1%. The findings are present in Table A 13 and Table A 16.

6.5. Out-of-Sample Predictability

In general, our out-of-sample predictions perform poorly. The R^2_{OOS}'s for the regressions with a monthly time horizon but without state-switching abilities are all negative, designated by N in Table 3.

Table 3 – Out-of-sample predictability excluding state-switching variables: Monthly data, Jan 2012 – Dec 2016, 60 observations

Dependent Variable	Explanatory Variable	R2oos
Denmark All Share	LMEX	N
Denmark All Share	BDI	N
Denmark Consumer Goods	BDI	N
Finland All Share	LMEX	N
Finland Industrials	LMEX	N
Norway All Share	BDI	N
Sweden All Share	BDI	N
Sweden Basic Materials	LMEX	N
Sweden Industrials	LMEX	N
Sweden Industrials	BDI	N

On a monthly time horizon with business cycle shifts 12 out of 22 R^2_{OOS}'s are positive ranging from 0,3% to a high of 6,7% for BDI on the Norway All Share Index. The four highest R^2_{OOS}'s on the regressions with a monthly time horizon, and state-switching abilities all have BDI as an explanatory variable. Results are shown in Table 4.

Table 4 – Out-of-sample predictability including state-switching variables: Monthly data, Jan 2012 – Dec 2016, 60 observations

Dependent Variable	Explanatory Variable	R2oos
Denmark All Share	LMEX	N
Denmark All Share	BDI	3,5%
Denmark Basic Materials	LMEX	N
Denmark Basic Materials	BDI	2,9%
Denmark Consumer Goods	LMEX	N
Denmark Consumer Goods	BDI	N
Denmark Industrials	LMEX	1,7%
Denmark Industrials	BDI	4,9%
Finland All Share	LMEX	0,3%
Finland Basic Materials	LMEX	0,6%
Finland Consumer Goods	LMEX	0,1%
Finland Consumer Goods	S&P	N
Finland Consumer Goods	Bloomberg	1,1%
Finland Industrials	LMEX	N
Norway All Share	LMEX	0,6%
Norway All Share	BDI	6,7%
Sweden All Share	BDI	N
Sweden All Share	LMEX	N
Sweden Basic Materials	LMEX	N
Sweden Basic Materials	BDI	N
Sweden Consumer Goods	LMEX	2,0%
Sweden Industrials	LMEX	N

The findings for weekly and daily time horizons for the R^2_{OOS} are found in Table A 14, Table A 15 and Table A 16 in the Appendix. On the regressions with weekly time horizon, three out of four R^2_{OOS}'s are negative both for the state-switching regressions and the regressions without state-switching abilities. On the daily level, we only observed predictability in the state-switching models. Six out of eight regressions have positive R^2_{OOS}'s ranging from 0,1% to 2,4%.

6.6. Portfolio Strategy

6.6.1. Portfolio Strategy Excluding State-Switching Variables

Eight portfolios are constructed for the monthly time horizon without the state-switching variables. The portfolios are distributed between all four countries. By looking at Table A 17, we observe that all of our portfolios get a negative return after five years and perform worse than their respective buy-and-hold portfolio for the corresponding index. The Sharpe ratios for the eight portfolios are all negative, but only five can be regarded as significantly worse than their respective buy-and-hold portfolios when analyzing the results of the Sharpe ratio tests.

Since the null hypothesis cannot be rejected for the remaining three portfolios, statistically, the Sharpe ratios cannot be regarded as worse than their buy-and-hold counterparts.

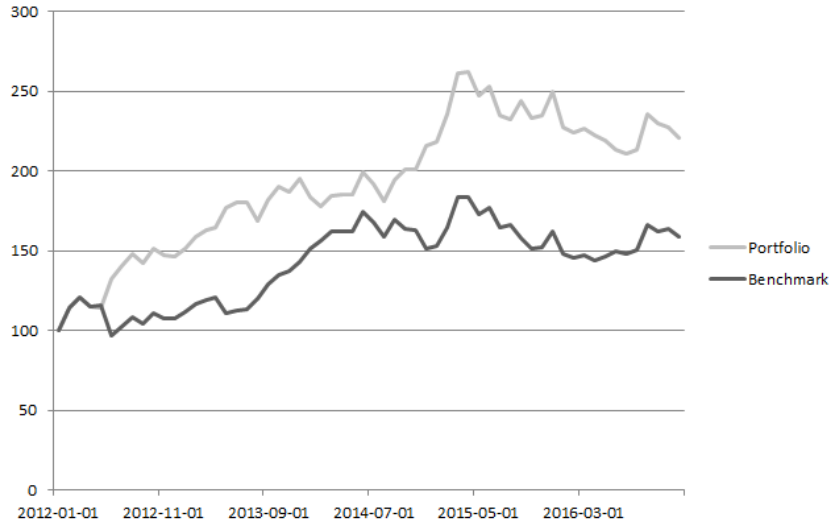
For the weekly time horizon, we construct two portfolios, one for the Sweden Consumer Goods Index and one for the Sweden Industry Index. Both indices are explained by Energy and S&P, and to account for the arising multicollinearity problem Energy is excluded from the regressions. The returns for both portfolios, as well as their Sharpe ratios, are inferior in comparison to their respective benchmark index, but only the Sharpe ratio for the Sweden Industry Index was significantly worse. The results are found in Table A 18.

No portfolios are constructed for daily data as none of the commodity indices can be used to predict any of the stock indices.

6.6.2. Portfolio Strategy Including State-Switching Variables

The findings from the portfolio strategy for all time horizons including state-switching variables are found in Table A 19, Table A 20 and finally in Table A 21. Regarding the monthly time horizon including state-witching variables, portfolios on all 13 indices are created. Interestingly, one portfolio, Denmark Industry, outperformed the buy-and-hold portfolio by 21 percentage units. The evolution of the portfolios can be studied in *Figure 1*. The Sharpe ratio for the portfolio is insignificantly higher. Our portfolio for the index Sweden Consumer Goods also performed well, earning a return equal to its benchmark index. When studying the fitted values for Sweden Consumer Goods, we can see that the values are all positive. This means that we always take a long position, creating a strategy equal to the buy-and-hold portfolio, and yielding the same return and resulting in the same Sharpe ratio. The remaining eleven portfolios are unable to yield a return equally large or higher than their benchmark index. Nine of the Sharpe ratios for our portfolios are lower than their counterparts of the buy-and-hold portfolios, but only one is significantly lower. Norway All Share and Denmark Industry achieved a higher Sharpe ratio than their respective benchmark ratio, but none at a significant level. Since both Bloomberg and S&P are significant for the Finland Consumer Goods, we exclude S&P from the regression to get rid of multicollinearity problems.

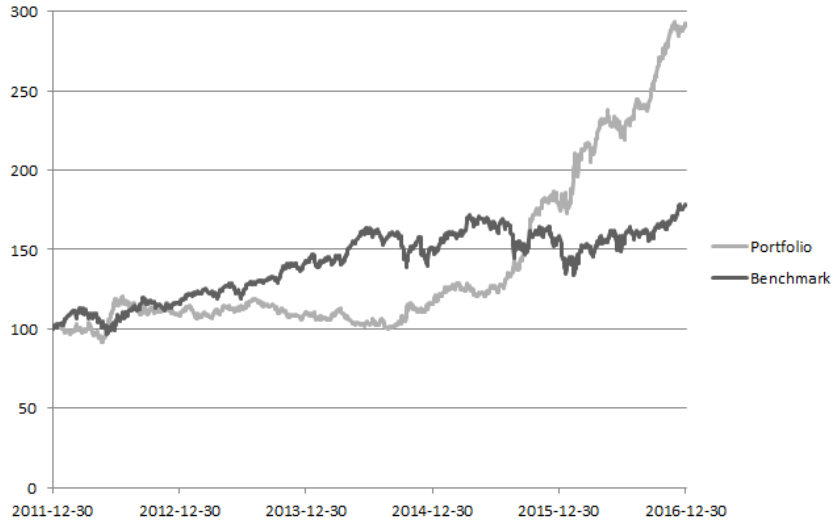
Figure 1 – State-switching model: Monthly returns 2012 – 2016 Denmark Industry



Finland Consumer Goods and Denmark Consumer Goods can both be explained by two of the commodity indices each for the weekly time horizon and portfolios are created accordingly. Both the return and the Sharpe ratio for Finland Consumer Goods exceed the respective values of its benchmark index. The Sharpe ratio is higher and insignificant. Our portfolio for Denmark Consumer Goods did not perform better than its benchmark index, and the Sharpe ratio for the portfolio is significantly lower than the Sharpe ratio of the benchmark index.

Three portfolios are created when including state-switching variables for daily data; these are the indices Norway All Share, Denmark Consumer Goods and Sweden Basic Materials. Our portfolio for Norway All Share yields a return as high as 193% compared to 78% for the benchmark index. The developments of the returns are shown in *Figure 2* below. Nevertheless, we cannot conclude that the Sharpe ratio is significantly higher. Our portfolios for Denmark Consumer Goods and Sweden Basic Materials both perform worse than their respective buy-and-hold portfolios. The Sharpe ratio for Sweden Basic Materials is the only one of the two which has a significant worse Sharpe ratio. As Sweden Basic Materials can be explained by Bloomberg, S&P, and Energy, we choose to only include Bloomberg to account for the multicollinearity problem.

Figure 2 – State-switching model: Daily returns 2012 – 2016 Norway All Share



6.6.3. Trading Strategy Summary

28 portfolios are created in an attempt to beat their respective benchmark index, but only three succeed in creating a higher return than their benchmark. Ten of our portfolios create a negative return. Four Sharpe ratios for our portfolios are greater than their benchmark, but none is significantly higher.

7 Analysis

The Efficient Market Hypothesis states that financial markets are unpredictable with stock prices following a random walk. The results from our empirical research give somewhat ambiguous indications of predictability existing on Nordic stock markets. When analyzing the outcomes from our regressions using a monthly time horizon, we can conclude that both the BDI and LMEX indices indicate significant in-sample predictability of equity index returns. When examining the results from our weekly and daily time horizons it is hard to find any clear patterns of predictability and the few signs of significance could easily be interpreted as coincidences related to the specific data series. Considering this, the subsequent parts of the analysis will focus on examining the results from the monthly regressions.

Even though significance could not be found in all sectors, BDI and LMEX are by far the best estimators of stock returns for our monthly data series. Considering previous studies in the field, these results are not surprising. When analyzing the predictability of the two variables, it is hard to find any specific pattern based on sector or country. The two broad stock indices S&P and Bloomberg, the Lumber Index, and the Energy Index cannot be said to have any in-sample prediction power on Nordic stock indices. Analyzing the inability to predict by these indices, we make the conclusion that they are too weighted against commodities that have little to none real influence on the future economic activity in the Nordic countries. Nevertheless, we find it odd that Lumber fails to predict the Swedish stock markets considering Sweden's high exposure towards the lumber sector.

Studying the results from our state-switching models further establishes the ideas of stock return predictions being highly cyclical. In line with previous research, we find that predictability in expansions is lost and only present in recessions. These results are particularly interesting considering that the number of observations for the recession state is substantially smaller. The size differences between the coefficients of the states are another significant feature of the state-switching models. Even though the expansion coefficients are insignificant, we can see a clear pattern of them being significantly smaller than the recession coefficients and in some cases also negative. This aligns well with the thesis of increasing commodity prices being better news for financial markets in recessions than in expansions.

From the computed R^2_{OOS}'s we clearly observe that our out-of-sample predictions perform worse than our in-sample predictions. Earlier research has found similar results, which indicate that the in-sample predictions give little exploitable information for an investor seeking profitable investment opportunities based on commodity return fluctuations. Even though predictability is found in-sample the case of low R^2_{OOS}'s is a clear argument for the validity of the Efficient Market Hypothesis since no prediction power can be found when testing the estimations on actual data. The distinctive difference between the ability to predict in and- out-of-sample and the reasons for this divergence is something that could be further investigated for the whole field of research concerning stock return predictability.

To further examine the validity of the Efficient Market Hypothesis we create portfolios based on the significant prediction power of the commodity indices. Only three out of 28 portfolios yield an excess return in comparison to a buy-and-hold position in the given index. As our R^2_{OOS}'s perform poorly overall, it is intuitive that our portfolios cannot render returns higher than their benchmark. Considering the low R^2_{OOS}'s any other results would have to be recognized as pure coincidence. Out of the 28 portfolios, none have a significantly greater Sharpe ratio than a regular buy-and-hold portfolio in the same index. Our findings of risk-adjusted returns give proof to Fama's theory of the impossibility of finding arbitrage opportunities on financial markets. Due to lack of observations in the weekly and monthly time horizons, we are unable to distinguish many of the Sharpe ratios as being lower, or higher, although large differences are studied between the two values. Finally, our results from the trading strategies are only theoretical. Including various costs associated with trading, such as transaction costs, cost inquiring when taking a short position and the liquidity problem in equities would have worsened our results.

8 Conclusion

We study the predictability power of commodity indices on Nordic equity indices using an in-sample period between 2000 and 2011 and an out-of-sample period between 2000 and 2016. In addition to univariate regression analysis were six commodity indices are tested for predictability on 13 different Nordic equity indices we also test for state-switching abilities of the commodity variables depending on the state of the business cycle. We also create a trading strategy based on the significance of our estimations. The study is conducted on daily, weekly and monthly stock returns.

From our findings, we conclude that the best predictors of monthly Nordic stock market returns are the Baltic Dry Index and the London Metal Exchange Index. We are not able to find predictability of daily and weekly stock returns. Strengthening the findings of previous research, we find that stock return predictions are highly cyclical. Predictability is found in recessions and disappears in expansions. We also find that the coefficients are considerably higher in the recession period indicating that increasing commodity prices are better news in recessions than in expansions. Our in-sample estimations perform badly in the out-of-sample period, and the portfolios created based on the significance of our findings fail to beat their relative benchmark indices in 25 out of 28 cases. None of the three portfolios that managed to beat a buy-and-hold position in their corresponding indices have a significantly higher risk-adjusted Sharpe ratio. Hence our findings are ambiguous regarding evidence in favor for or against the theory of efficient markets.

The field of commodities ability to forecast stock returns is nowhere near exhausted. The relationship can be studied for new markets, and different commodities as each country have unique exposures to the commodity markets. Further, we want to stress the inability of stock return predictors to operate as good estimator's out-of-sample and suggest future research to explore the reasons to this even further.

In our study, we focus on the isolated effect of commodities ability to predict stock market returns. Additional studies could explore the predictability of commodities in a setting with more variables to see if this would enhance the performance of out-of-sample predictions and trading strategies. Moreover, we have found evidence pointing in the direction of the London Metal Exchange Index not being the only commodity index with coefficients switching sign

depending on the state of the business cycle as stated by Jacobsen et al. (2016). The ability to switch sign, and the reason for why some commodities switch sign and not others, is also a field that could be further researched.

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Appendix

Table A 1 – Variables retrieved from Thomson Reuters Datastream

Commodity Indices	Datastream Code
LMEX Index	LMEINDX
S&P GSCI Energy Index	GSENSPT
S&P GSCI Commodity Index	GSCISPT
Baltic Dry Index	BALTICF
Bloomberg Commodity Index	DJUBSTR
Lumber Index	CSCRLCT
Stock Indices	
OMX Stockholm	SWSEALI
OMX Copenhagen	COSEASH
OMX Helsinki	HEXINDX
Oslo Børs All Share Index	LOSLOASH
OMX Stockholm Basic Materials	OSX1BML
OMX Copenhagen Basic Materials	OCX1BML
OMX Helsinki Basic Materials	OHX1BML
OMX Stockholm Industrials	OSX1IDL
OMX Copenhagen Industrials	OCX1IDL
OMX Helsinki Industrials	OHX1IDL
OMX Stockholm Consumer Goods	OSX1CGL
OMX Copenhagen Consumer Goods	OCX1CGL
OMX Helsinki Consumer Goods	OHX1CGL
Control Variable	
S&P 500	S&PCOMP

Table A 2 – Variables retrieved from various platforms

Country	CPI	Governement Bond 10Y
Sweden	Statistics Sweden	Swedish Riksbank
Denmark	Statistics Denmark	Swedish Riksbank
Finland	Statistics Finland	Swedish Riksbank
Norway	Statistics Norway	Swedish Riksbank

Variable	CFNAI	One month Swedish Treasury Bill
Platform	Federal Reserve Bank of Chicago	Swedish Riksbank

Table A 3 – Stationarity Test: Monthly data

	Intercept		Intercept and Trend	
Null Hypothesis: variable has a unit root	**t-Statistic**	**Prob.**	**t-Statistic**	**Prob.**
Bloomberg Commodity Index	-12,6	0,000	-12,8	0,000
S&P GSCI Commodity Index	-11,7	0,000	-11,8	0,000
Baltic Dry Index	-12,1	0,000	-12,0	0,000
S&P GSCI Energy Index	-11,7	0,000	-11,7	0,000
LMEX Index	-11,9	0,000	-11,8	0,000
Lumber Index	-13,9	0,000	-13,8	0,000
OMX Stockholm	-12,4	0,000	-12,5	0,000
OMX Copenhagen	-11,3	0,000	-11,3	0,000
OMX Helsinki	-12,0	0,000	-12,1	0,000
Oslo Exchange Benchmarket	-11,7	0,000	-11,7	0,000
OMX Stockholm Basic Materials	-12,0	0,000	-12,0	0,000
OMX Copenhagen Basic Materials	-12,0	0,000	-13,3	0,000
OMX Helsinki Basic Materials	-13,6	0,000	-13,6	0,000
OMX Stockholm Industrials	-12,9	0,000	-12,9	0,000
OMX Copenhagen Industrials	-14,4	0,000	-11,7	0,000
OMX Helsinki Industrials	-11,9	0,000	-11,9	0,000
OMX Stockholm Consumer Goods	-12,6	0,000	-12,6	0,000
OMX Copenhagen Consumer Goods	-13,3	0,000	-10,2	0,000
OMX Helsinki Consumer Goods	-11,1	0,000	-11,1	0,000
CPI Sweden	-3,4	0,013	-4,2	0,000
CPI Denmark	-11,4	0,000	-6,4	0,000
CPI Finland	-3,4	0,013	-11,4	0,000
CPI Norway	-13,0	0,000	-13,0	0,000
Government Bond 10 year Sweden	-4,7	0,000	-5,2	0,000
Government Bond 10 year Denmark	-9,3	0,000	-9,6	0,000
Government Bond 10 year Finland	-10,1	0,000	-8,6	0,000
Government Bond 10 year Norway	-9,8	0,000	-10,0	0,000
S&P 500	-13,5	0,000	-13,6	0,000

Table A 4 – Stationarity Test: Weekly data

	Intercept		Intercept and Trend	
Null Hypothesis: variable has a unit root	**t-Statistic**	**Prob.**	**t-Statistic**	**Prob.**
Bloomberg Commodity Index	-29,4	0,000	-29,6	0,000
S&P GSCI Commodity Index	-29,8	0,000	-29,8	0,000
Baltic Dry Index	-18,7	0,000	-18,7	0,000
S&P GSCI Energy Index	-29,8	0,000	-29,9	0,000
LMEX Index	-30,5	0,000	-30,5	0,000
Lumber Index	-27,7	0,000	-27,7	0,000
OMX Stockholm	-30,9	0,000	-30,9	0,000
OMX Copenhagen	-19,3	0,000	-19,3	0,000
OMX Helsinki	-31,0	0,000	-31,1	0,000
Oslo Exchange Benchmarket	-30,0	0,000	-30,0	0,000
OMX Stockholm Basic Materials	-31,0	0,000	-31,0	0,000
OMX Copenhagen Basic Materials	-30,3	0,000	-30,2	0,000
OMX Helsinki Basic Materials	-31,5	0,000	-31,5	0,000
OMX Stockholm Industrials	-32,3	0,000	-32,3	0,000
OMX Copenhagen Industrials	-19,5	0,000	-19,5	0,000
OMX Helsinki Industrials	-30,0	0,000	-30,0	0,000
OMX Stockholm Consumer Goods	-29,8	0,000	-29,8	0,000
OMX Copenhagen Consumer Goods	-28,5	0,000	-28,5	0,000
OMX Helsinki Consumer Goods	-29,7	0,000	-29,7	0,000
CPI Sweden	n/a	n/a	n/a	n/a
CPI Denmark	n/a	n/a	n/a	n/a
CPI Finland	n/a	n/a	n/a	n/a
CPI Norway	n/a	n/a	n/a	n/a
Government Bond 10 year Sweden	-12,5	0,000	-12,6	0,000
Government Bond 10 year Denmark	-9,6	0,000	-9,7	0,000
Government Bond 10 year Finland	-9,3	0,000	-9,4	0,000
Government Bond 10 year Norway	-15,3	0,000	-15,2	0,000
S&P 500	-31,8	0,000	-31,9	0,000

Table A 5 – Stationarity Test: Daily data

	Intercept		Intercept and Trend	
Null Hypothesis: variable has a unit root	**t-Statistic**	**Prob.**	**t-Statistic**	**Prob.**
Bloomberg Commodity Index	-68,4	0,000	-68,4	0,000
S&P GSCI Commodity Index	-69,4	0,000	-69,4	0,000
Baltic Dry Index	-21,0	0,000	-21,0	0,000
S&P GSCI Energy Index	-69,6	0,000	-69,6	0,000
LMEX Index	-71,2	0,000	-71,2	0,000
Lumber Index	-60,6	0,000	-60,6	0,000
OMX Stockholm	-67,1	0,000	-67,1	0,000
OMX Copenhagen	-63,1	0,000	-63,1	0,000
OMX Helsinki	-66,5	0,000	-66,5	0,000
Oslo Exchange Benchmarket	-66,5	0,000	-66,5	0,000
OMX Stockholm Basic Materials	-65,7	0,000	-65,7	0,000
OMX Copenhagen Basic Materials	-65,5	0,000	-65,5	0,000
OMX Helsinki Basic Materials	-62,2	0,000	-62,2	0,000
OMX Stockholm Industrials	-65,2	0,000	-65,2	0,000
OMX Copenhagen Industrials	-63,3	0,000	-63,2	0,000
OMX Helsinki Industrials	-63,4	0,000	-63,4	0,000
OMX Stockholm Consumer Goods	-65,5	0,000	-65,5	0,000
OMX Copenhagen Consumer Goods	-62,9	0,000	-62,9	0,000
OMX Helsinki Consumer Goods	-64,7	0,000	-64,7	0,000
CPI Sweden	n/a	n/a	n/a	n/a
CPI Denmark	n/a	n/a	n/a	n/a
CPI Finland	n/a	n/a	n/a	n/a
CPI Norway	n/a	n/a	n/a	n/a
Government Bond 10 year Sweden	n/a	n/a	n/a	n/a
Government Bond 10 year Denmark	n/a	n/a	n/a	n/a
Government Bond 10 year Finland	n/a	n/a	n/a	n/a
Government Bond 10 year Norway	n/a	n/a	n/a	n/a
S&P 500	-51,4	0,000	-51,5	0,000

Table A 6 – Correlation Matrix: Monthly data

	Bloomberg	S&P	BDI	S&P Energy	Lumber	LMEX	Bond Denmark	Bond Finland	Bond Norway	Bond Sweden	S&P 500	CPI Denmark	CPI Finland	CPI Norway
S&P	92%													
	0,000													
BDI	27%	30%												
	0,000	0,000												
S&P Energy	85%	98%	29%											
	0,000	0,000	0,000											
Lumber	31%	30%	13%	27%										
	0,000	0,000	0,063	0,000										
LMEX	69%	59%	20%	51%	25%									
	13,092	10,255	2,813	8,232	3,618									
Bond Denmark	11%	18%	6%	19%	2%	14%								
	1,493	2,513	0,830	2,670	0,230	1,960								
Bond Finland	9%	18%	5%	20%	-3%	6%	83%							
	1,302	2,477	0,690	2,835	-0,398	0,889	20,375							
Bond Finland	9%	17%	5%	19%	2%	14%	55%	61%						
	0,197	0,015	0,528	0,008	0,802	0,054	0,000	0,000						
Bond Sweden	8%	17%	2%	18%	1%	10%	60%	85%	63%					
	0,273	0,021	0,798	0,010	0,844	0,172	0,000	0,000	0,000					
S&P 500	40%	37%	19%	32%	36%	47%	7%	4%	8%	10%				
	0,000	0,000	0,010	0,000	0,000	0,000	0,360	0,605	0,254	0,155				
CPI Denmark	27%	29%	0%	28%	0%	15%	0%	6%	12%	4%	-2%			
	0,000	0,000	0,949	0,000	0,946	0,035	0,985	0,391	0,108	0,580	0,765			
CPI Finland	29%	33%	14%	34%	7%	15%	5%	7%	12%	6%	3%	69%		
	0,000	0,000	0,051	0,000	0,341	0,039	0,528	0,318	0,100	0,440	0,673	0,000		
CPI Norway	18%	21%	3%	21%	3%	10%	2%	1%	1%	-3%	1%	48%	38%	
	0,013	0,004	0,712	0,003	0,647	0,168	0,818	0,924	0,910	0,729	0,897	0,000	0,000	
CPI Sweden	29%	33%	11%	33%	6%	14%	6%	12%	15%	8%	4%	65%	62%	50%
	0,000	0,000	0,115	0,000	0,431	0,051	0,426	0,107	0,035	0,298	0,602	0,000	0,000	0,000

Table A 7 – Correlation Matrix: Weekly data

	BDI	Bloomber	S&P	S&P Energy	Lumber	LMEX	Bond Denmark	Bond Finland	Bond Norway	Bond Sweden
Bloomberg	7%									
	0,038									
S&P	7%	90%								
	0,035	0,000								
S&P Energy	7%	82%	98%							
	0,057	0,000	0,000							
Lumber	7%	-2%	0%	2%						
	0,036	0,605	0,973	0,660						
LMEX	3%	65%	49%	38%	2%					
	0,452	0,000	0,000	0,000	0,623					
Bond Denmar	1%	5%	3%	3%	-2%	0%				
	0,675	0,116	0,312	0,357	0,617	0,975				
Bond Finland	1%	5%	4%	3%	-2%	0%	100%			
	0,683	0,114	0,274	0,316	0,518	0,944	0,000			
Bond Norway	2%	6%	4%	3%	-1%	0%	97%	97%		
	0,506	0,079	0,290	0,330	0,774	0,998	0,000	0,000		
Bond Sweden	3%	7%	5%	4%	0%	1%	99%	98%	98%	
	0,406	0,040	0,174	0,213	0,960	0,719	0,000	0,000	0,000	
S&P 500	2%	32%	28%	25%	7%	39%	-7%	-7%	-7%	-6%
	0,474	0,000	0,000	0,000	0,040	0,000	0,034	0,035	0,041	0,064

Table A 8 – Correlation Matrix: Daily data

	BDI	Bloomberg	S&P	S&P Energy	Lumber	LMEX
Bloomberg	3%					
	0,060					
S&P	3%	90%				
	0,049	0,000				
S&P Energy	3%	83%	98%			
	0,077	0,000	0,000			
Lumber	1%	12%	10%	8%		
	0,474	0,000	0,000	0,000		
LMEX	2%	58%	43%	33%	12%	
	0,280	0,000	0,000	0,000	0,000	
S&P 500	-1%	25%	24%	22%	14%	27%
	0,702	0,000	0,000	0,000	0,000	0,000

Table A 9 – Univariate model including control variables and lagged dependent variable: Monthly data, Jan 2000 – Dec 2011, 142 observations

Dependent Variable	Explanatory Variable	P-value	Coefficient	C	Adj R-squared
Denmark All Share	LMEX	0,032	0,160	0,0034	15%
Denmark All Share	BDI	0,043	0,041	0,0036	15%
Denmark Consumer Goods	BDI	0,046	0,053	0,0035	19%
Finland All Share	LMEX	0,040	0,250	-0,0013	4%
Finland Industrials	LMEX	0,006	0,270	0,0042	14%
Norway All Share	BDI	0,018	0,068	0,0058	14%
Sweden All Share	BDI	0,017	0,058	0,0024	9%
Sweden Basic Materials	LMEX	0,023	0,239	0,0030	13%
Sweden Industrials	LMEX	0,010	0,250	0,0036	9%
Sweden Industrials	BDI	0,017	0,066	0,0046	8%

Table A 10 – Univariate model including control variables and lagged dependent variable: Weekly data, Jan 2000 – Dec 2011, 624 observations

Dependent Variable	Explanatory Variable	P-value	Coefficient	C	Adj R-squared
Sweden Consumer Goods	Energy	0,003	-0,078	0,003	2%
Sweden Consumer Goods	S&P	0,005	-0,097	0,003	2%
Sweden Industrials	S&P	0,023	-0,097	0,006	3%
Sweden Industrials	Energy	0,025	-0,073	0,006	3%

Table A 11 – State-switching model including control variables and lagged dependent variable: Monthly data, Jan 2000 – Dec 2011, 142 observations

Dependent Variable	Explanatory Variable	Autocorrelated	Rec P-value	Rec Coefficient	Exp P-value	Exp Coefficient	C	Adj R-squared
Denmark All Share	LMEX	No	0,000	0,425	0,879	-0,013	0,005	22%
Denmark All Share	BDI	No	0,009	0,074	0,912	0,003	0,004	16%
Denmark Basic Materials	LMEX	No	0,022	0,428	0,430	0,118	0,001	7%
Denmark Basic Materials	BDI	No	0,012	0,117	0,574	-0,028	0,002	8%
Denmark Consumer Goods	LMEX	No	0,001	0,497	0,916	0,012	0,005	23%
Denmark Consumer Goods	BDI	No	0,000	0,138	0,384	-0,033	0,005	24%
Denmark Industrials	LMEX	No	0,002	0,467	0,612	-0,063	0,005	17%
Denmark Industrials	BDI	No	0,048	0,080	0,951	0,003	0,004	12%
Finland All Share	LMEX	No	0,005	0,490	0,552	0,086	0,000	6%
Finland Basic Materials	LMEX	No	0,017	0,424	0,861	0,026	0,002	8%
Finland Consumer Goods	LMEX	No	0,000	0,522	0,464	-0,074	0,006	20%
Finland Consumer Goods	S&P	No	0,031	0,282	0,798	0,025	0,005	11%
Finland Consumer Goods	Bloomberg	No	0,038	0,333	0,603	-0,076	0,005	12%
Finland Industrials	LMEX	No	0,000	0,567	0,443	0,086	0,006	19%
Norway All Share	LMEX	No	0,007	0,374	0,846	0,024	0,006	15%
Norway All Share	BDI	No	0,000	0,139	0,528	-0,027	0,007	19%
Sweden All Share	BDI	No	0,024	0,073	0,291	0,038	0,003	9%
Sweden All Share	LMEX	No	0,004	0,363	0,895	0,014	0,003	10%
Sweden Basic Materials	LMEX	No	0,002	0,458	0,472	0,089	0,004	15%
Sweden Basic Materials	BDI	No	0,041	0,078	0,855	0,008	0,004	12%
Sweden Consumer Goods	LMEX	Yes	0,018	0,266	0,775	-0,026	0,004	8%
Sweden Industrials	LMEX	No	0,008	0,481	0,348	0,100	0,005	11%

Table A 12 – State-switching model including control variables and lagged dependent variable: Weekly data, Jan 2000 – Dec 2011, 684 observations

Dependent Variable	Explanatory Variable	Rec P-value	Rec Coefficient	Exp P-value	Exp Coefficient	C	Adj R-squared
Denmark Consumer Goods	Lumber	0,045	0,251	0,997	0,000	0,003	2%
Denmark Consumer Goods	BDI	0,021	0,093	0,446	0,014	0,002	2%
Finland Consumer Goods	BDI	0,001	0,082	0,645	0,011	0,004	3%
Finland Consumer Goods	LMEX	0,021	0,142	0,048	-0,090	0,004	3%

Table A 13 – State-switching model including control variables and lagged dependent variable: Daily data, Jan 2000 – Dec 2011, 3128 observations

Dependent Variable	Explanatory Variable	Rec P-value	Rec Coefficient	Exp P-value	Exp Coefficient	C	Adj R-squared
Sweden Basic Materials	Bloomberg	0,856	-0,013	0,002	0,092	0,00001	7%
Sweden Basic Materials	LMEX	0,922	0,005	0,019	0,060	0,00001	7%
Sweden Basic Materials	S&P	0,265	-0,050	0,005	0,056	0,00001	7%
Sweden Basic Materials	Energy	0,178	-0,043	0,018	0,035	0,00001	7%
Norway All Share	Bloomberg	0,144	0,093	0,000	0,118	0,00011	10%
Norway All Share	S&P	0,345	0,041	0,000	0,087	0,00011	9%
Norway All Share	Energy	0,304	0,033	0,000	0,065	0,00011	9%
Denmark Consumer Goods	BDI	0,003	0,061	0,887	-0,003	0,00011	5%

Table A 14 – Univariate model excluding control variables and lagged dependent variable: Weekly data, Jan 2000 – Dec 2011, 684 observations

Dependent Variable	Explanatory Variable	P-value	Coefficient	C	Adj R2	R2oos
Sweden Consumer Goods	Energy	0,010	-0,066	0,003	0,9%	N
Sweden Consumer Goods	S&P	0,018	-0,079	0,003	0,7%	N
Sweden Industrials	S&P	0,018	-0,098	0,006	0,7%	0,1%
Sweden Industrials	Energy	0,021	-0,074	0,006	0,7%	N

Table A 15 – State-switching model excluding control variables and lagged dependent variable: Weekly data, Jan 2000 – Dec 2011, 684 observations

Dependent Variable	Explanatory Variable	Rec P-value	Rec Coefficient	Exp P-value	Exp Coefficient	C	Adj R2	R2oos
Denmark Consumer Goods	Lumber	0,001	0,250	0,844	0,009	0,0006	1,5%	0,4%
Denmark Consumer Goods	BDI	0,001	0,093	0,674	0,011	0,0005	1,5%	N
Finland Consumer Goods	BDI	0,001	0,078	0,7629	0,007	0,0007	1,4%	N
Finland Consumer Goods	LMEX	0,001	0,187	0,1009	-0,071	0,0007	1,8%	N

Table A 16 – State-switching model excluding control variables and lagged dependent variable: Daily data, Jan 2000 – Dec 2011, 3128 observations

Dependent Variable	Explanatory Variable	Rec P-value	Rec Coefficient	Exp P-value	Exp Coefficient	C	Adj R2	R2oos
Sweden Basic Materials	Bloomberg	0,134	0,066	0,001	0,120	4,9E-07	0,4%	0,2%
Sweden Basic Materials	LMEX	0,185	0,043	0,001	0,084	4,2E-06	0,4%	N
Sweden Basic Materials	S&P	0,571	0,017	0,005	0,072	-5,8E-07	0,2%	0,4%
Sweden Basic Materials	Energy	0,793	0,006	0,021	0,044	3,6E-06	0,1%	0,4%
Norway All Share	Bloomberg	0,002	0,124	0,000	0,130	8,8E-05	0,7%	1,1%
Norway All Share	S&P	0,008	0,074	0,000	0,090	8,5E-04	0,6%	0,1%
Norway All Share	Energy	0,007	0,058	0,000	0,066	8,8E-05	0,6%	2,4%
Denmark Consumer Goods	BDI	0,006	0,058	0,723	-0,008	1,0E-04	0,2%	N

Table A 17 – Trading Portfolio: Monthly data excluding state-switching variables, Jan 2012 – Dec 2016, 60 observations

Sweden Industry

	Coefficient	P-value
Coefficient	0,00086	
Metals	0,20011	0,018
BDI	0,04595	0,086

	Trading Portfolio	Buy-Hold
Return	-58%	95%
Sharpe Ratio	-0,66	0,58
z-value	4,49	
p-value	0,000	

Sweden Basic Materials

	Coefficient	P-value
Coefficient	-0,00024	
Metals	0,25358	0,004

	Trading Portfolio	Buy-Hold
Return	-39%	97%
Sharpe Ratio	-0,12	0,22
z-value	1,56	
p-value	0,059	

Sweden All Share

	Coefficient	P-value
Coefficient	-0,00047	
BDI	0,05488	0,021

	Trading Portfolio	Buy-Hold
Return	-36%	74%
Sharpe Ratio	-0,17	0,25
z-value	2,08	
p-value	0,019	

Norway All Share

	Coefficient	P-value
Coefficient	0,00265	
BDI	0,06596	0,012

	Trading Portfolio	Buy-Hold
Return	-27%	78%
Sharpe Ratio	-0,16	0,21
z-value	2,07	
p-value	0,019	

Finland Industry

	Coefficient	P-value
Coefficient	0,00091	
Metals	0,29994	0,000

	Trading Portfolio	Buy-Hold
Return	-26%	85%
Sharpe Ratio	-0,07	0,23
z-value	1,37	
p-value	0,085	

Finland All Share

	Coefficient	P-value
Coefficient	-0,00365	
Metals	0,20232	0,047

	Trading Portfolio	Buy-Hold
Return	-24%	66%
Sharpe Ratio	-0,06	0,20
z-value	1,12	
p-value	0,131	

Denmark Consumer Goods

	Coefficient	P-value
Coefficient	0,00198	
BDI	0,08492	0,002

	Trading Portfolio	Buy-Hold
Return	-31%	198%
Sharpe Ratio	-0,09	0,46
z-value	2,55	
p-value	0,005	

Denmark All Share

	Coefficient	P-value
Coefficient	0,00049	
Metals	0,15689	0,092
BDI	0,05708	0,054

	Trading Portfolio	Buy-Hold
Return	-43%	122%
Sharpe Ratio	-0,18	0,33
z-value	2,57	
p-value	0,005	

Table A 18 – Trading Portfolio: Weekly data excluding state-switching variables, Jan 2012 – Dec 2016, 261 observations

Sweden Consumer Goods

	Coefficient	P-value
Coefficient	0,00023	
S&P	-0,07919	0,018

	Trading Portfolio	Buy-Hold
Return	-8%	112%
Sharpe Ratio	-0,01	0,15
z-value	2,12	
p-value	0,017	

Sweden Industry

	Coefficient	P-value
Coefficient	0,00040	
S&P	-0,09810	0,639

	Trading Portfolio	Buy-Hold
Return	20%	95%
Sharpe Ratio	0,09	0,25
z-value	n/a	
p-value	n/a	

Table A 19 – Trading Portfolio: Monthly data including state-switching variables, Jan 2012 – Dec 2016, 60 observations

Denmark All Share

	Coefficient	P-value
Coefficient	0,00191	
Metals EXP	0,03266	0,695
BDI EXP	-0,00295	0,923
Metals REC	0,43578	0,000
BDI REC	0,02944	0,332

	Trading Portfolio	Buy-Hold
Return	75%	122%
Sharpe Ratio	0,24	0,33
z-value	0,700	
p-value	0,242	

Denmark Basic Materials

	Coefficient	P-value
Coefficient	-0,00074	
Metals EXP	0,07270	0,601
BDI EXP	-0,38903	0,444
Metals REC	0,29463	0,112
BDI REC	0,09997	0,050

	Trading Portfolio	Buy-Hold
Return	92%	235%
Sharpe Ratio	0,23	0,42
z-value	0,94	
p-value	0,174	

Denmark Consumer Goods

	Coefficient	P-value
Coefficient	0,00346	
Metals EXP	0,06402	0,538
BDI EXP	-0,04543	0,233
Metals REC	0,47889	0,001
BDI REC	0,11487	0,003

	Trading Portfolio	Buy-Hold
Return	59%	198%
Sharpe Ratio	0,17	0,36
z-value	1,15	
p-value	0,125	

Denmark Industry

	Coefficient	P-value
Coefficient	0,00132	
Metals EXP	-0,00132	0,991
BDI EXP	-0,00810	0,852
Metals REC	0,51445	0,001
BDI REC	0,03760	0,385

	Trading Portfolio	Buy-Hold
Return	99%	78%
Sharpe Ratio	0,23	0,19
z-value	0,28	
p-value	0,490	

Finland All Share

	Coefficient	P-value
Coefficient	-0,00263	
Metals EXP	0,03705	0,782
Metals REC	0,41894	0,007

	Trading Portfolio	Buy-Hold
Return	-33%	66%
Sharpe Ratio	-0,14	0,20
z-value	1,32	
p-value	0,093	

Finland Basic Materials

	Coefficient	P-value
Coefficient	-0,00137	
Metals EXP	0,02561	0,853
Metals REC	0,47256	0,003

	Trading Portfolio	Buy-Hold
Return	-29%	95%
Sharpe Ratio	-0,04	0,18
z-value	1,19	
p-value	0,117	

Finland Consumer Goods

	Coefficient	P-value
Coefficient	0,00337	
Metals EXP	-0,03341	0,757
Bloomberg EXP	0,04134	0,683
Metals REC	0,72275	0,000
Bloomberg REC	-0,23657	0,191

	Trading Portfolio	Buy-Hold
Return	27%	57%
Sharpe Ratio	0,10	0,16
z-value	0,34	
p-value	0,367	

Finland Industry

	Coefficient	P-value
Coefficient	0,00224	
Metals EXP	0,08534	0,413
Metals REC	0,58122	0,000

	Trading Portfolio	Buy-Hold
Return	-18%	85%
Sharpe Ratio	-0,05	0,23
z-value	1,27	
p-value	0,102	

Norway All Share

	Coefficient	P-value
Coefficient	0,00376	
Metals EXP	0,03126	0,768
BDI EXP	-0,03129	0,420
Metals REC	0,27709	0,051
BDI REC	0,09926	0,011

	Trading Portfolio	Buy-Hold
Return	65%	78%
Sharpe Ratio	0,24	0,21
z-value	0,20	
p-value	0,421	

Sweden All Share

	Coefficient	P-value
Coefficient	0,00001	
Metals EXP	0,02149	0,091
BDI EXP	0,01985	0,565
Metals REC	0,27892	0,938
BDI REC	0,04174	0,577

	Trading Portfolio	Buy-Hold
Return	-40%	74%
Sharpe Ratio	-0,21	0,25
z-value	2,33	
p-value	0,001	

Sweden Basic Materials

	Coefficient	P-value
Coefficient	0,00110	
Metals EXP	0,06491	0,440
BDI EXP	-0,00976	0,600
Metals REC	0,42451	0,989
BDI REC	0,03818	0,436

	Trading Portfolio	Buy-Hold
Return	35%	97%
Sharpe Ratio	0,11	0,22
z-value	0,59	
p-value	0,278	

Sweden Consumer Goods

	Coefficient	P-value
Coefficient	0,00126	
Metals EXP	-0,00231	0,980
Metals REC	0,30166	0,005

	Trading Portfolio	Buy-Hold
Return	112%	112%
Sharpe Ratio	0,33	0,33
z-value	n/a	
p-value	n/a	

Sweden Industry

	Coefficient	P-value
Coefficient	0,00183	
Metals EXP	0,06814	0,532
Metals REC	0,44387	0,001

	Trading Portfolio	Buy-Hold
Return	-14%	95%
Sharpe Ratio	-0,04	0,25
z-value	1,26	
p-value	0,104	

Table A 20 – Trading Portfolio: Weekly data including state-switching variables, Jan 2012 – Dec 2016, 261 observations

Finland Consumer Goods

	Coefficient	P-value
Coefficient	0,0008	
Metals EXP	-0,0708	0,101
BDI EXP	0,0042	0,860
Metals REC	0,1591	0,006
BDI REC	0,0668	0,006

	Trading Portfolio	Buy-Hold
Return	59%	57%
Sharpe Ratio	0,07	0,07
z-value	0,03	
p-value	0,512	

Denmark Consumer Goods

	Coefficient	P-value
Coefficient	0,0007	
Lumber EXP	0,0083	0,848
BDI EXP	0,0109	0,686
Lumber REC	0,2127	0,005
BDI REC	0,0792	0,005

	Trading Portfolio	Buy-Hold
Return	10%	198%
Sharpe Ratio	0,02	0,17
z-value	2,03	
p-value	0,021	

Table A 21 – Trading Portfolio: Daily data including state-switching variables, Jan 2012 – Dec 2016, 1305 observations

Norway All Share

	Coefficient	P-value
Coefficient	0,0000881	
Bloomberg Exp	0,130071	0,101
Bloomberg Rec	0,123845	0,860

	Trading Portfolio	Buy-Hold
Return	193%	78%
Sharpe Ratio	0,08	0,05
z-value	0,96	
p-value	0,169	

Denmark Consumer Goods

	Coefficient	P-value
Coefficient	0,0007	
Lumber EXP	0,0083	0,848
BDI EXP	0,0109	0,686
Lumber REC	0,2127	0,005
BDI REC	0,0792	0,005

	Trading Portfolio	Buy-Hold
Return	69%	198%
Sharpe Ratio	0,04	0,07
z-value	1,50	
p-value	0,067	

Sweden Basic Materials

	Coefficient	P-value
Coefficient	0,0007	
Lumber EXP	0,0083	0,848
BDI EXP	0,0109	0,686
Lumber REC	0,2127	0,005
BDI REC	0,0792	0,005

	Trading Portfolio	Buy-Hold
Return	-31%	97%
Sharpe Ratio	-0,01	0,07
z-value	1,94	
p-value	0,026	