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Economic forces and the OMXS30

A study of economic variables' ability to predict stock returns on the OMXS30

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Abstract

This paper investigates whether the information from a number of different economic variables have the ability to predict stock returns on the OMXS30. The estimated forecast models are evaluated with a number of standard metrics to find the best performing models. These models are then used in combination with two portfolio strategies and tested over different time periods and forecast horizons, thereby giving an insight into the economic value of the underlying forecast models actual performance. The economic results are then compared with a benchmark model consisting of a simple buy and hold strategy to find the best performing combination of portfolio strategies and forecast models.

Generally, none of the used economic variables are found to be a consistent predictor over all time periods, even though a few managed portfolios succeed in outperforming the buy and hold strategy over some specific time periods, only one portfolio (Switch Rec Bivariate OilExch 1 month) outperforms the buy and hold over all time periods. In the end we conclude that our findings are not conclusive enough to verify whether the final outcomes of the successful portfolio management strategies are the case of 'good' forecasting, or that of randomness and luck.

Keywords: Forecasting, Portfolio Management, Stock Returns, OMXS30

Table of Contents

1. Introduction

Research into the relationship between economic factors and equity returns has been conducted since the latter part of the 1970s. Intuitively, this relationship is a rather appealing one. After all, it is not an unreasonable assumption that macroeconomic and financial variables should have an impact on stock returns, considering that they should affect firms' costs, future investment opportunities and consumption and thus, in turn have an effect on firm profits.

However, so far the previous research has had difficulties providing anymore than little support for the desired relationship, despite numerous studies of the relationship between equity returns and an abundance of economic variables. The only variables to seemingly have a significant impact on equity returns throughout the extant literature is the negative impact from inflation, first observed by Fama (1981), and the observed effects of money related variables. Generally, the economic factors used throughout the literature seem to provide contradictory evidence, one study finds evidence for a significant relationship between a variable and the equity returns, while another similar study using the same variable, finds no such evidence. For example, Hyde and Kappel (2009) found industrial production growth to be one of the variables able to predict stock returns in Germany, while in comparison, Flannery and Protopapadakis (2002) found industrial production to have no significant impact on stock returns at all. Despite a rich history of research, the majority is carried out on American markets, and before Asprem (1989) international evidence was sorely lacking. Since then, a number of studies have focused on markets outside the U.S. but the supply of international evidence is still considered rather limited.

The purpose of this paper lines up with the history of previous research, and is therefore divided into two parts. First, we will follow the focus of early research in examining whether a relationship between economic factors and the stock market actually exists. Our second and main purpose however, reflects the focus of the more recent literature, and will thus analyse if information from economic variables can be used to construct predictive models. After all, following the reasoning by Guidolin et al. it seems to be a reasonable focus;

"Nevertheless, a true test of the usefulness of a model in describing data, and therefore in informing market agents or policy makers, must be its ability to forecast."

- Guidolin et al (2009) pp.2

We will follow the approach of Stock and Watson (2003) and Hyde and Kappel (2009) and study the out-of-sample forecasts of stock returns, testing numerous economic variables and combinations, through the use of linear regression models over different forecast horizons and using both a recursive and rolling window approach in the estimation process. We also investigate the performance of our forecast models using both "switch" and "long/short" portfolio strategies and thereby gain an insight into the de facto economic value of our forecast models.

Our results indicate that the estimated linear regression models using combinations of significant variables, including the lag of stock returns, are able to predict future stock returns 'better' than a benchmark model consisting of only lagged observations of the stock returns. The variables we find most interesting are used in models with a recursive window estimation approach and are: the difference between the long (10 year) and short (3 month) interest rates and the oil price. We are however unable to find any clear evidence, for any combination of variables, that are consistently able to forecast better than the benchmark model over all sample periods. On the other hand, we manage to provide some evidence that portfolios, following simple management strategies, offer superior performance compared to a buy and hold strategy over the full out-of-sample forecasted period 2003:01-2012:12. The evaluated portfolio strategies that resulted in the highest final net wealth were both based on forecast models estimated through a recursive approach. These two portfolios were: The money supply *m1* over a three month forecast horizon and the oil price *OilExch* over a one month forecast horizon.

The continuation of the paper is organized as follows: In section 2, we present a literature review. Section 3 describes our methodology and econometric approach. Section 4 presents our data. Section 5 presents our empirical results. Finally, in section 6 we conclude.

2. Literature Review

Fama (1981) observed a negative relationship between inflation and stock returns, which he explained as a consequence of proxy effects where the negative relationship between stock returns and inflation is explained by a negative relationship between stock returns and measures of real activity since both inflation and stock returns are strongly related toward future real activity in the economy. Geske and Roll (1983) continued researching the relationship between inflation and stock returns, finding it most puzzling. They consider the empirical evidence contradictory to economic theory, as well as common sense, and thereby do not consider the empirically observed relationship a causal one. They disagree with the explanation presented by Fama (1981) and instead consider stock returns to be the first link in a chain of events, where a higher rate of monetary expansion and a simultaneous negative relationship toward expected inflation results in changes in real activity, in turn resulting in money supply growth changes which affect inflation.

James, Koreisha and Partch (1985) tests this proposed chain of events simultaneously step-by-step, using a VARMA-analysis. Their results support the reversed causality model proposed by Geske and Roll (1983) and find stock returns to signal changes in expected inflation and nominal interest rates. Lee (1992) find stock returns to explain only a small part of the observed variation when interest rates are introduced into the VAR model – which disagrees with James, Koreisha and Partch (1985). Lee also finds inflation to only explain a small part of the variation in real activity, despite the fact that real activity reacts negatively to inflation shocks, and his results thereby support the explanation presented by Fama (1981) rather than the chain events of Geske and Roll (1983). However, Lee (1992) find no causal link between stock returns and money supply, implying no such link between inflation and stock returns resulting in the conclusion that the negative relationship between stock returns and inflation would most likely not play a reliable role in predictive models.

Chen, Roll and Ross (1986) were one of the first to consider multiple economic variables in their research into the relationship between economic factors and the asset market. They argue;

"Any systematic variables that affect the economy's pricing operator or that influence dividends would also influence stock market returns. Additionally, any variables that are

necessary to complete the description of the state of nature will also be part of the systematic risk factors." - Chen, Roll and Ross (1986) pp.384

They considered all variables that they used to have an a priori relationship toward systematic asset risks and numerous (*yield curve twists, unanticipated and expected inflation, industrial production and changes in risk premium)* were found significant in explaining asset returns. Chen, Roll and Ross (1986) also found the value weighted-index for the New York Stock Exchange to prove insignificant in explaining expected stock returns when it was set against the economic variables used by the authors. Especially interesting when considering that the index proved significant in explaining a portion of the variability in the time-series data of stock returns. Fama (1990) on the other hand managed to explain 30% of the variance of the annual returns on the value-weighted New York Stock Exchange with a proxy variable consisting of economic and financial factors, attempting to capture expected returns and shocks therein, and another 43% using growth rates of production, which is a good measure for shocks to expected cash flows. Combining the two variables he managed to explain 58% of the annual return variance of the index. Following the results of Fama (1990) it is therefore not surprising that Chen, Roll and Ross in a final conclusion states that; …"*stock returns are exposed to systematic economic news, that they are priced in accordance with their exposure, and that the news can be measured as innovations in state variables whose identification can be accomplished through simple and intuitive financial theory." – Chen, Roll and Ross (1986) pp.402*

McQueen and Roley (1990) questions the results of previous research, where macroeconomic news were found having only a small effect on stock prices. By allowing for different cycles in the economy they manage to find evidence for stronger relationships. Their empirical results are especially interesting for variables measuring real economic activity where stock prices during a '*strong*' economy react negatively to positive news in such a variable. Boyd, Hu and Jagannathan (2002) find similar results but are mostly interested in employment. They find unemployment positively correlated with stock prices during 'good times' and showing negative correlation during '*bad times'*. Fama and French (1989) also found evidence for how business cycles create variations in how macroeconomic information affects stock prices and expected returns. In general, they found expected returns lower during '*good times'* and vice versa.

Until Asprem (1989) examined the relationship between macro variables and stock prices in ten European countries, there had been an absence of international evidence. He observed an inverse relationship between stock prices and employment, imports, inflation and interest rates. He also found a positive relationship between stock prices and expectations about future real activity, measures for money and the U.S. yield curve. Lamont (1999) used economic tracking portfolios to study the relationship between stock prices and economic variables while Jiranykul (2009) studied the relationship between four macroeconomic variables *(Real GDP, money supply, nominal effective exchange rate* and *inflation)* and the stock index in Thailand. Flannery and Protopapadakis (2002) use a GARCH approach in their search for compelling evidence for whether any real macroeconomic variables have an impact on equity returns. Out of seventeen macro variables tested, six were found to be strong candidates (*CPI, PPI, Balance of Trade, Employment/Unemployment* and *Housing starts*). Interestingly, popular real economic activity measures, such as industrial production and real GNP, were not found among the strong candidates.

Jiranykul (2009) used two tests for cointegration; where the Johansen cointegration test was successful, while the Engle-Granger test failed, in finding cointegration. Referring to previous research, he concluded that the study found cointegration and therefore also evidence for a long run relationship between the four macro-variables and the Thai stock market. Lamont (1999) found his out-of-sample results, using monthly data and tracking 12-months changes ahead in target macro variables, suggesting that tracking portfolios will be useful for hedging and forecasting with macro-economic variables. Asprem (1989) also found support for the possibility of predictive models by observing several instances where stock prices were found to be related to the historic values of economic variables. The results of Jiranykul (2009), Lamont (1999) and Asprem (1989) suggests the possibility to either create or improve forecast models for asset returns using macroeconomic data.

Stock and Watson (2003) tests for predictive relationships between asset prices and the two variables output and inflation. Hyde and Kappel (2009) follow the methodology of Stock and

Watson and examines if macroeconomic factors can be used to forecast returns on the German stock and bond markets. Stock and Watson (2003) found numerous problems in the expected predictive relationship, but regarded these problems as limitations on econometric procedures and conventional models, rather than implying the absence of such relationships. One underlying assumption in macroeconomics is after all the premise that asset prices and interest rates contain information regarding future economic development. Hyde and Kappel (2009) on the other hand found real activity, oil prices and changes in short-term interest rates significant when predicting German stock returns. They also found evidence for the exchange rate and inflation to be somewhat relevant. By evaluating the forecast models with both economic interpretations, as well as a battery of standard metrics, they found that the preferred models offered considerable market timing and yield economically significant results for long/short stratagems.

Maio and Phillip (2012) examine whether macroeconomic factors in fact drive returns on stock and bond markets which by extension would make it possible to predict these returns. Ang and Bekaert (2001) asks whether stock returns in the US, France, The UK and Japan can be predicted using three financial instruments; *The earnings yield, short rate* and *dividend yield*. Rapach, Wohar and Rangvid (2005) examined the stock returns for twelve industrialized countries and whether macroeconomic variables (measures for; *inflation, industrial production, money stock, unemployment and various interest rates*) are able to predict these returns. Guidolin et al. (2009) examine the performance of both linear, as well as non-linear, predictive models for equity returns in the G7 countries. Maio and Phillip (2012), despite utilizing data from 124 macro-variables as well as numerous different VAR specifications and theories, found macroeconomic information to only play a marginal and rather insignificant role in predictive models already consisting of the financial variables commonly used in the return decomposition literature.

Ang and Bekaert (2001) found the short rate, independent of sample period, to be significant at the 99% level and remarkably robust in the short run regarding its impact on equity premiums (Where a 1% increase in annual short rate decreases the equity premium with around 3,7%). Despite this, all three tested variables were found to completely lack in predictive power over the long run. Rapach, Wohar and Rangvid (2005) found evidence for a limited predictive ability over asset returns in general. However, they found industrial production and inflation to be especially limited in predictive ability while term spread, inflation and the money stock exhibited a stronger predictive ability for some of the industrialized countries. Furthermore, interest rates were found to be most reliable and consistent and exhibited significant results for all countries – a result reminding of Ang and Bekaert (2001). Guidolin et al. (2009) found the U.S. and U.K. markets to have '*richer*' data making it possible to utilize non-linear models, which in some cases forecasted rather well. The same could not be said of the data from the markets in France, Germany and Italy. Here the best-performing forecasts were instead found to be those of simple benchmark models, such as, random walks and univariate auto-regressions. However, no model was found that consistently outperformed the market. They also found that the best model changes, sometimes suddenly, for different horizons, countries and markets.

3. Methodology

3.1 Introduction to Methods

This paper mainly follows the approach of Stock and Watson (2003) and Hyde and Kappel (2009) and is divided into two main parts. In the first part we analyze whether there are any long term relationships between Swedish stock returns and 19 economic variables, depicting macroeconomic as well as financial information. The second part connects to the main focus of this paper: whether economic information can be used to actually predict stock prices and thereby earn abnormal returns. Since our paper is divided into two different purposes we require a wide range of different methods. For the first part we use simple and multivariate regression models to see whether a relationship between the independent variables and the OMXS30 actually exist. In the second part, we construct a wide number of forecast models and evaluated their performance using a battery of standard metrics, as well as using different portfolio strategies to apply an economic interpretation of our results.

For the constructions of econometric models and tests we mainly used EViews 7.1 and for the forecasts models we used GRETL (1.9.12) for recursive window forecasts, and EViews with the roll add-in, for rolling window forecasts.

3.2 Analysis of Long Term Relationships

3.2.1 Simple Linear Regression Model

Following Stock and Watson (2003), we perform a simple linear autoregressive model to see how much of the variation of the returns on OMXS30 that can be explained by previous observations. We estimate:

$$y_{t+h} = \alpha + \gamma(L)y_t + \varepsilon_{t+h}.$$

The equation above depicts the univariate regression model and will be further explained in section 3.2. The regression model uses a linear approach to look for correlation between OMXS30 and its own lags. y_{t+h} represent OMXS30 *h* period(s) ahead of time *t,* and is the observation we later wish to predict. $\gamma(L)y_t$ is OMXS30 at time *t* and (L) is the polynomial for the use of lags in the model. ε_{t+h} is the error term at time *t+h*. Following the approach of Stock and Watson (2003) we use lags for the previous twelve months, and L is thereby equal to 12.

We use the six OLS assumptions (Westerlund 2005) to make sure that our model fulfills the requirements for BLUE (best linear unbiased estimation). These assumptions are:

1) The Model is Linear with an intercept

The true model that reflects the underlying population should be linear with an intercept.

2) Expected value of the residuals is equal to zero, $E(\varepsilon_i) = 0$

Important since it shows that the estimated errors are caused by variation in εi and correct in the long runt since the sum of all residuals will amount to zero, that is: $E(\varepsilon_i) = 0$

3) Var(ε_i) $=$ constant (heteroskedasticity)

If there is heteroskedasticity in the model, the variance will change over time resulting in incorrect standard errors and thereby making it impossible to perform hypothesis testing with any certainty. If heteroskedasticity is found, the model is no longer BLUE since there are estimators with a lower variance. Should such a problem arise, we will use the Whites estimator to get correct standard errors thereby.

4) $\varepsilon_i, \varepsilon_j$ is independent (Autocorrelation).

Our error terms are only independent if their covariance equals zero and if the covariance differ from zero our model suffers from autocorrelation. If that is the case, our error terms would no longer be independent from each other which causes the value at time t to be depending on the value at t-1 and so forth. Our observations will thereby be correlated, and there will exist better models for estimating our data. We use the Breusch-Godfrey test in EViews to check our model for autocorrelation.

5) No perfect relationship in independent variables

The Independent variables cannot be perfectly correlated with each other and must take the form of at least two different values. Having perfectly correlated independent variables gives multicolinearity.

6) ε_i is normally distributed $e_i \sim N(0, \sigma^2)$

The sixth assumption requires the error-terms to be normally distributed. We use the Jarque-Bera test in EViews, and since our sample is large enough, we should not suffer from any normality problems. We look for misspecification in the model by performing a Ramsey's RESET test which look for non-linearity in the model and check for non included correlated variables.

We also look for non-stationarity in the variables before running the OLS estimation. If the variables exhibit non-stationarity, or have unit root, it would result in previous observations affecting current ones, by one or more. Thereby, the shocks of this effect would last forever and never recede completely, which in effect makes the model infinitively large given sufficient time. Thus, OLS can produce invalid estimates giving a spurious regression with a high R^2 value and low DW value even if the variables might be fully uncorrelated in reality. We check for non-stationarity using the augmented dickey fuller test, and correct for it using either the first or second differentiation of the variable. (Westerlund 2005)

3.2.2 Multivariate Linear Regression Model

In addition to the simple linear regression analysis, which only takes into account the effect on OMXS30s returns from its own lags, we will also apply a multivariate regression model to analyze the changes in OMXS30s returns. In our multivariate regression model we introduce independent variables depicting forces in the economy, both macroeconomic as well as financial variables, to see if we can construct a model which is more adept and thereby able to explain a larger portion of the variation in the data, R^2. A larger adjusted R^2 would mean that adding variables of forces in the economy would help our model to explain movements in stock prices.

The multivariate regression model is constructed using the General-to-Specific approach, where the initial model begin by including all 19 variables and the first twelve lags of each variable. The lags thereby contain the monthly values over the previous year for each of the 19 variables, making the lag polynomial (L) equal to twelve (just as in the simple model). We then, step-by-step, remove the worst performing non-significant variable until the model only include significant variables.

Initial Multivariate Linear Regression Model:

$$\begin{aligned} OMXS30_{t+h} = \alpha + {} & \beta_1(L)CPI_t + \beta_2(L)CCI_t + \beta_3(L)term\ spread_t + \beta_4(L)oilexch_t \\ & + \beta_5(L)trade\ balance_t + \beta_6(L)short\ term_t + \beta_7(L)Ind\ prod_t \\ & + \beta_8(L)M1_t + \beta_9(L)unemp_t + \beta_{10}(L)energyCPI_t + \beta_{11}(L)OMXS30_t \\ & + \beta_{12}(L)CLI + \beta_{13}(L)gold_t + \beta_{14}(L)prodtendancy_t + \beta_{15}(L)rexch_t \\ & + \beta_{16}(L)M0_t + \beta_{17}(L)X_t + \beta_{18}(L)vac_t + \beta_{19}(L)bnkrptp_t \\ & + \beta_{20}(L)CCIswe93_t + \varepsilon_{t+h} \end{aligned}$$

3.3 Forecast Methods

3.3.1 Forecast Models

We follow Stock and Watson (2003) and will thereby use linear regressions and out-of-sample forecasting in our approach toward estimating predictive models. Our data ranges from 1986:02 – 2012:12 and we use the period 1986:02-2002:12 as the in-sample period used for estimating forecast models over the out-of-sample period 2003:01-2012:12. Since we already know how our variables will behave in the out-of-sample period, we are able to properly and immediately evaluate the ability and accuracy of our forecasts. We use four different models in our attempts to forecast the returns on OMXS30. These models will consist of Univariate, Bivariate and Trivariate auto regression models, as well as the best multivariate regression model estimated in part 3.1.3. The final multivariate model is included to see whether the model we found to best explain returns on the OMXS30 might outperform the auto regression models when forecasting the returns.

Following Stock and Watson (2003) we also use two different approaches for our estimated models, and therefore use both a rolling window as well as a recursive approach for our models. Rolling window uses a pre-specified number of previous observations, creating a 'window' of observation, which is allowed to move with the forecast into the future by including the newly estimated variable. Simply stated, if we use a 'window' of ten observations to forecast the eleventh observation then, once the eleventh observation is estimated, we move the window by dropping the first observation and include the real eleventh observation, and use these ten observations to forecast the twelfth observation. This continues until all desired observations are predicted. Recursive estimation on the other hand expands the estimation window for each and every forecasted variable, giving the model more data for each new forecast.

Previous research found that different variables were significant over different periods of time and performed well over different horizons. Following these results we have decided to use three different time horizons, *h,* when applying our different forecast models. We will use one month, three months and six months for these different forecast horizons. The different horizons we have chosen also seem reasonable if we regard a personal investor, who lacks the time or interest to frequently update their portfolio, and has a long run investment horizon.

Following the Efficient Market Hypothesis (EMH) we use the univariate model for OMXS30 as our benchmark model. EMH states that markets are informationally efficient and comes in three different stages; the weak form states that all past public information is contained in asset prices, the semi-strong states that prices will change instantly to reflect all new publicly available information and the third, and final, strong form which states that prices contain, and instantly changes to reflect all new information, both public and hidden. If the EMH or the random walk hypothesis, which claims that stock prices follow a random walk and cannot be predicted, holds, it would be a good guess that the price today will also be the price tomorrow. Following that, either all publicly (and hidden) information is already depicted in the price, or stock prices follow random movements which are impossible to predict. Our benchmark model will therefore only consist of the dependent variable OMXS30 and use lags of OMXS30 for the previous twelve months as independent variables, thus making it an AR(12)-model and identical to the simple linear regression we estimated in part 3.1.2. and is thereby estimated following the equation:

$$\mathrm{OMXS30}_{\mathrm{t+h}} = \alpha + \gamma(\mathrm{L})\mathrm{OMXS30}_{\mathrm{t}} + \varepsilon_{\mathrm{t+h}}$$

3.3.2 Course of action

In an attempt to use only the most relevant variables in our forecasts models, we will only include the variables that exhibited a significant relationship toward the dependent variable given the included lag length. We used a fixed lag length of twelve lags for all variables in the models, but since all variables might not exhibit correlation toward the dependent variable, we will first use a joint F-test. We performed 20 joint F-tests, one for each variable and its twelve lags, to see which of our independent variables that actually exhibit a correlated relationship towards the dependent variable, OMXS30. Only those variables exhibiting a significant relationship in the joint F-test were later used to estimate forecasting models. We also check all forecast models for heteroskedasticity using a Breusch-Pagan-Godfrey test, if found, we correct the standard errors using the HAC Newey-West.

The bivariate model uses OMXS30 as dependent variable while a combination of OMXS30 lags and a second economic variable are used as independent variables. The equation below depicts the bivariate model, where X represents the independent economic variable used;

$$OMXS30_{t+h} = \alpha + \gamma(L)OMXS30_t + \beta(L)X_t + \varepsilon_{t+h}$$

The trivariate models are constructed in the same manner as the bivariate, the only difference is that we add a third variable to the model, variable Z;

$$OMXS30_{t+h} = \alpha + \gamma(L)OMXS30_t + \beta_1(L)X_t + \beta_2(L)Z_t + \varepsilon_{t+h}$$

3.4 Evaluation Methodologies of Forecasting Performance

3.4.1 Standard metric tests

We are looking at four different measures for evaluating the forecast performance of our models: The root mean squared forecast error, the mean squared forecast error, the absolute forecast error and Theil's U. The results of all these measurements are all presented in relative terms compared to the benchmark model. The measurements are transformed into relative terms using the equation for relative mean squared forecast error, which can be seen below. Following Stock and Watson (2003) we will primarily focus on the Relative mean squared forecast error which is calculated using the forecast result of the benchmark model and comparing this result with that of our forecast models. In the following equations *b* depicts the benchmark model, while *m* is the forecast model in question. T_1 is the first date of the observations used in the forecast and T_2-*h* is the last observation used minus the prediction horizon, *h*.

Relative mean squared forecast error:

$$Relative\ MSFE_h = \frac{\frac{1}{T_1 - T_2 - h}\sum_{T_1}^{T_2 - h}(y_{t+h} - \hat{y}_{t+h}^{m})^2}{\frac{1}{T_1 - T_2 - h}\sum_{T_1}^{T_2 - h}\left(y_{t+h} - \hat{y}_{t+h}^{b}\right)^2}$$

Root means squared (forecast) error:

$$RMSFE_h = \sqrt{\frac{1}{T_1 - T_2 - h}\sum_{t=T_1}^{T_2 - h}(y_{t+h} - \hat{y}_{t+h})^2}$$

The root mean squared error is the difference between the forecasted mean and the actual observations which are then squared and rooted. We add this performance measure to evaluate whether taking the root, and letting our model be punished to a lesser extent by outliers, will in fact change the performance measure of our models.

Theil's U:

$$U = \sqrt{\frac{1}{T_1 - T_2 - h} \frac{\sum_{T_1}^{T_2-h} \left(\frac{\hat{y}_{t+h} - y_{t+h}}{y_t}\right)^2}{\sum_{T_1}^{T_2-h} \left(\frac{y_{t+h} - y_t}{y_t}\right)^2}}$$

Theil's U is a measurement which compares our forecasted models against a minimal historic data forecast model. Forecasting with minimal historical data means that we only have today's value y_t as a predictor for the future value y_{t+h}. The interpretation is quite straightforward and is presented in the table below, where naïve forecasting is the estimation technique where todays observations are used to forecast tomorrow, without any adjustments. This is commonly used as a comparison to more sophisticated forecasting models.

Theil's U statistic	Interpretation
Less than 1	The forecasting technique is better than naïve forecasting
1	The forecasting technique is equal to naïve forecasting
More than 1	The forecasting technique is worse than naïve forecasting

Mean absolute error:

$$MAE_h = \frac{1}{T_1 - T_2 - h} \sum_{t=T_1}^{T_2-h} |y_{t+h} - \hat{y}_{t+h}|$$

We also add the mean absolute error, since it is a evaluation measure that uses neither squared or rooted evaluation errors, but instead the absolute values. The MAE give us more statistically robust values against outliers, and is a good compliment to the MSFSE.

3.4.2 Economical performance of forecasting models

Following Hyde and Kappel (2009) we construct a number of different portfolios, following two different portfolio strategies, and covering three different time horizons (one, three and six months). These portfolios are constructed to supply an economic interpretation of the forecasts models, giving us a clear measure of how well our models actually perform in terms of money. We will also considering three different time periods for our evaluations:

- Full sample 2003:01-2012:12
- Sub-sample(1) 2003:01-2007:12
- Sub-sample(2) 2008:01-2012:12

We have two main reasons for using sub-samples as well as the full sample. First, prior research (Stock and Watson 2003) found that variables that are good predictors for one certain period might not, in fact, be a good predictor for another period. Secondly, we expect the state of the overall economy and its markets to be different prior and post the financial crisis of 2008. Thus, we wish to identify predictors that perform well during both the 'good' times (prior to the financial crisis), as well as those that perform well during 'bad' times (post the financial crisis).

We will also use two different portfolio strategies, a switching and a 'long/short' strategy, which will be applied on each forecast model. In the *switching strategy* we invest 100% of the money in stocks (in our case the OMXS30 index) if the forecast for *h*-step ahead indicates a positive return, or invest 100% of the money in bonds, if the *h*-step ahead forecast indicates a negative return on stocks. In an attempt to connect our portfolio strategy to the real world, we will apply an arbitrarily chosen trade cost for each switch, amounting to 25 basis points of the portfolio value.
In the *long/short stratagem* we "hold long" if the forecast indicates positive returns *h*-step ahead. If the forecasting indicates negative returns the stocks are sold as a future/forward where the holder is obligated to buy at time *t+h* at the price at time *t.* If the stocks are sold, we will instantly re-invest all money in stocks for the price at *t+h*. This is a purely theoretical strategy where we ignore any other costs associated with future/forward contracts. However, we will apply a transaction cost of 25 points for when we buy stocks at time *t+h.* The main idea behind the futures is that if the random walk hypothesis is true, there is no way to predict stock prices, and people might be willing to buy at $price_t$ at time *t+h* to avoid risk. To be able to see if the different portfolios and strategies hold any economic gains and worth undertaking we will compare them with a simple buy and hold strategy. If any portfolio performs worse than the simple buy and hold, it has failed miserably.

Each portfolio starts with a capital of 10 000 SEK and is managed according to its strategy using the forecasted values as triggers for any action undertaken. Since the models are forecasted over three different horizons (one, three and six months) this will also impact our portfolio stratagems e.g. the portfolio for the six month forecasting model will be updated once every sixth month during its holding period.

3.4.3 Limitations of the Management Strategies

Both of our strategies are dependent on a number of simplified theoretical assumptions which, once applied in a practical manner, causes a number of limitations for analyzing the results. The applied transaction cost of 25 basis points of the portfolio value, might in reality be too high or too low, and chosen arbitrarily to not punish the management strategies more than necessary. A higher transaction cost would be advantageous for the buy and hold strategy, which is something that should be considered when interpreting the results.

The portfolio strategies are also constructed for simplicity, where the smallest negative or positive indication results in 100% switches in assets, making the strategies rather extreme in their execution. Thus, a more balanced way to handle the indications given by the forecasts would be to only trade the assets if the forecasted values are over/under a predefined bound, making sure only larger forecasted deviations from zero triggers a trade. Another way to handle the portfolio strategies in a less extreme manner would be to trade a smaller part of the total assets when the forecasts indicates smaller returns and larger parts when the forecast indicates large returns, negative or positive. We also assume that all transactions in our model are frictionless, which is a rather unlikely assumption in reality. In for example the long/short strategy we assume that there is always a buyer willing to hold the short contract at the predefined price, without any additional fee.

Further on we pick the portfolios to manage through a number of measurements, focusing on the lowest mean forecast errors, when in reality one of the most important parts of portfolio management is timing the market, e.g. in the switch strategy, where a market drop of 25% for one month will have a smaller impact on the MFSE than the difference between the forecasted returns, of 1% and -1%, for the month in question. The MFSE value will thereby only increases with the value between the two forecasts, while the new wealth will be affected by -25% if the forecast indicates positive returns or give a moderate positive return equal to the bond rate if the forecast indicate a negative return. The drop in the market will thereby largely affect our net return, while it will hardly affect our MFSE, making the measure somewhat misleading at times.

3.4.4 Evaluation of Economic Performance

The performance of the portfolios is evaluated using three different measures; the Sharpe ratio, Jensen's Alpha and the Final net wealth. The total net wealth is the final wealth of the portfolio subtracting any incurred trading costs over the managed period. We will also look at the monthly mean return and the standard deviation.

Sharpe's Ratio:

$$\frac{r_p - r_f}{\sigma_p}$$

Where r_p is the return on the portfolio, r_f the risk free interest rate, and σ_p the standard deviation of portfolio returns. For simplicity, we ignore the risk-free rate and look at the mean return over its own standard deviation. The Sharpe's ratio enables us to compare mean returns after they have been compensated for the risk of the portfolio.

Jensen's Alphas:

$$\alpha_p = \bar{r}_p[\, r_f + \beta_P(r_m - r_f)]$$

Where $\bar{r}_p$ is the portfolio return, r_f the risk free interest rate, β_P the beta of the portfolio and r_m the market return. We look for positive Jensen's alphas since they would indicate abnormal returns in relation to the rate of returns of the OMXS30.

4. Data

4.1 Gathering and Adjusting Data

We gathered data using Thomson Reuters DataStream for a number of variables that according to previous studies, or economic intuition, had the potential to exhibit some ex ante relationship toward stock returns. Since we used Thomson as our data mining tool, we have numerous different original sources for our variables, such as OECD, NIER, Statistics Sweden and so forth. However, since we consider Thomson to be a capable and trustworthy client for data gathering, we will not go into these different original sources any further. The data was gathered using monthly observations covering the range 1986:01-2012:12. A data range sufficient for our purpose to estimate forecast models using the period 1986-2002, and then using the remaining out-of-sample period 2003-2012 for evaluating our models performance. We found few variables with earlier observations (Before 1986) and we also had to reject a number of potential variables since they lacked data, were only available for annual observations, had been cancelled during our data range or simply did not exist as publicly available information in Sweden.

All gathered data covers the entire period except for exports (1990-2012) and the Swedish consumer confidence indicator (1993-2012). The short term interest rate (3 month SSVX) was only available in quarterly observations. We considered the short-term rate as fixed for all three months in every quarterly observation and used that assumption to adjust the quarterly observations into monthly. Oil and gold prices were only available in foreign currency and we used the exchange rates to adjust the data into SEK to avoid exchange rate fluctuations, so increases in price would depend on changes in price of the underlying asset. All our data was gathered in different formats; i.e. indices, percentages and historical levels. By re-setting all index based observation to 1986:01, making this observation equal 100, we could adjust all data into one homogenous format; the change in percentage terms between each month. Our data thereby contain 21 measures of economic factors, adjusted into monthly percentage growth rates.

We also gathered data for the one, three and six month bid yields using three different bond indices. The yields were quoted in yearly rates and discounted into monthly yields to be used in the economic interpretation part of our portfolio evaluation. These rates will thereby not be used in estimating our models.

4.2 Independent variables

The table below summarises all 21 variables (which can be seen in Table 4.1) used in our data set. Since the variable LRr_SRr contain the information from the Short_term and Long10y we thereby have a dataset of 19 explanatory variables. OMXS30 represent the stock index for the 30 most traded firms on the Nasdaq OMX Nordic Stockholm exchange. The stock index acts both as dependent and independent variable, since we use previous (lagged) values when estimating of our models.

Table 4.1 Independent variables

Variable	Definition
OMXS30	Index for the Swedish stock exchange
CPI	Consumer Price Index Sweden
CCI	American Consumer Confidence Indicator
CCISWE93	Swedish Consumer Confidence Indicator
Short_term	3 month SSVX
Long10y	10y SSVX
LRr_SRr	Difference between interest rates of 3 month SSVX and 10 year SSVX
Oilexch	World USD price/barrel. Adjusted by SEK/USD exchange rate into Swedish Kronor
Rexch	The real effective Swedish exchange rate
bnkrptp	Bankruptcy
vtb	Visible trade balance
X	Swedish exports
Ind_prod	Industry Production Index Sweden
EnergyCPI	Consumer Price Index for housing, water, electricity, gas and other fuels
Vac	Reported vacancies on the Swedish job market with a work period lasting more than 10 days which has not been filled at the end of a month
Unemp	Unemployment Sweden.
M0	Measure of Money supply in Sweden
M1	Measure of Money supply in Sweden
Gold	Gold price in USD per Troy Ounce on the London Bullion Market
prodtendency	OECD measurement of production tendency in the manufacturing sector
CLI	OECD Composite Leading Indicators Sweden

4.2.1 Oil and Energy prices

Increasing oil prices could potentially increase firm costs, resulting in smaller room for investments and lowering profits. Some firms will be more sensitive to oil price shocks than others, determined by the firm's dependence of oil in the production process. Sweden have no domestic oil production making Sweden more sensitive toward oil price shocks, since all oil used have to be imported, in comparison to oil producing countries. Higher oil prices will most likely effect household consumption when for example increased production costs will be pushed on toward consumers or gasoline prices rise.

Previous research mainly found a significant relationship between oil prices and stock returns, but there have been varying results where for example Chen, Roll and Ross (1986) found oil to be systematically priced and having no overall effect on asset prices. Whereas Cheung and Ng (1998) found that measures of aggregated real activity, such as real oil prices, exhibit a cointegrated relationship toward five different stock market indices and that such measures yield information regarding stock returns not already contained in classically used financial measures. Cobo-Reyes and Pérez Quirós (2005) investigate oil prices and its relationship to industrial production as well as stock returns in order to figure out which of these (*industrial production and stock returns*) exhibits a stronger relation to oil price shocks. They find empirical evidence for a significant and negative relationship between oil price shocks and both variables, but found the relation between stock returns and oil prices to be the stronger relation of the two. Hyde and Kappel (2009) found changes in oil price to be one of the key predictors for German stock returns.

We also believe, using the same arguments as for oil, that energy prices are another candidate for having a relationship toward stock returns. The energy CPI use the U.N classification of individual consumption according to purpose into account, and looks at a CPI bundle defined by costs for housing, water, electricity, gas and other fuels (Thomson). Our original idea however was to use data for the development of energy prices in Sweden, unfortunately we were unable to find such a series covering our period, but we believe that the energy CPI have the potential to fill that role.

4.2.2 Consumer Confidence Indicators

Consumer Confidence Indicators are generated from a survey over consumer's expectations and plans regarding the present and future state of the economy and conducted by the National Institute of Economic Research (Konjunkturinstitutet) since 1979 and before that (since 1973) by Statistics Sweden (Statistiska Centralbyrån). However, we were only able to retrieve data reaching back to 1993, when the survey changed from being performed quarterly to monthly. Realizing we would not find data for the entire period, we also incorporated the CCI for the U.S. We argue that, if the Swedish measure would lack the required number of observations needed to find a connection to OMXS30, then U.S. CCI could be used as an alternate to its equivalent Swedish measure. Considering the U.S. as the world leader and Sweden a small and open economy depending in exports and imports, it is plausible that the U.S. CCI could reflect the Swedish CCI, at least to a degree.
The CCI in Sweden is conducted once every month trough 1500 phone interviews with people between the ages 16-84. The interviewees are asked questions concerning personal finances, plans to buy consumer durables and their present, and future twelve month, view on the state of the Swedish economy. The CCI is later calculate as the average of the balances from the answers given in the interviews and thereby create a speedy and

qualitative measure for the overall consumer confidence (Konjunkturinstitutet Webpage 2013). In other words; before/during 'bad times' the CCI will be lower than before/during 'good times' and we therefore expect a positive growth in CCI to indicate consumption increases, followed by rising firm profits and higher stock returns, while negative growth is expected to indicate the opposite.

4.2.3 Gold Price

We are also interested in testing whether the gold price might have a relationship toward stock returns. We believe gold to be regarded as a rather safe investment alternative from the investor's point of view and that it holds the potential to substitute, or at least complement, CCI as a measure for overall confidence in the economy (and markets). We therefore expect increases in the gold price, at least larger ones, to reflect an increasing uncertainty in the stock market and to exhibit a negative relationship toward returns.

4.2.4 Inflation

Inflation measures the change in the general purchasing power of the domestic currency over a period of time and is classically measured through the Consumer Price Index. The CPI represents a generalized consumption bundle, and measures inflation by observing price changes within this predefined bundle. When the general price level in the economy rises, the same amount of currency will now allow you to consume less than before in real terms. The Swedish Central Bank (Riksbanken) legislated to keep the inflation stable around 2% (the rate considered synonymous with price stability) through the use of mainly the repo rate (Fregert and Jonung 2005). If the production gap (output – trended output) is negative the inflationary pressure is usually low which results in lowered interest rates, too avoid too low inflation, and stimulates the economy (Eklund 2007).

Inflation has been found having a relationship toward stock returns in the extant literature. Fama(1981) found inflation and stock returns to be negatively related which Geske and Roll(1983) explained by a chain of events, resulting in a higher rate of monetary expansion, and later supported by the empirical evidence of James, Koreisha and Partch(1985). Lee(1992) on the other hand disagrees with Geske and Roll(1983) and James, Koreisha and Partch(1985) and instead found his results to support the theory Fama(1981). Flannery and Protopapadakis (2002) as well as Jiranykul (2009) also found inflation to be playing a strong part in explaining equity returns. Generally, inflation seems to be one of few variables that show compelling evidence of actually exhibiting a relationship toward stock returns in the extant literature.

4.2.5 Industrial Production Index and Production Tendency

Industrial Production Index, compounded by Statistics Sweden (SCB) and the Production Tendency Survey (OECD) are both measures of the real activity in the economy. They portray the changes in production in Sweden over the specified time, and thereby reflect the state of the economy. Asprem (1989) found a positive relationship between stock prices and expectations on future real activity, while Fama (1990) managed to explain 43% of the variance in stock returns to be explained by the growth rate of production and Hyde and Kappel (2009) found industrial production growth able to predict future stock returns.

4.2.6 Unemployment and Vacancies

Unemployment is defined as the difference between the part of the population currently part of the workforce and the part currently employed. High rates of unemployment are followed by high societal costs in the shape of decreasing tax incomes, unemployment benefits and losses in production, since the output during high unemployment is smaller than potential output (Eklund 2007). In the extant literature Boyd, Hu and Jagannathan (2002) found increases in unemployment to, in general, indicate falling stock prices during busts and increasing stock prices during booms.

Vacancies on the other hand is a measure of all unfilled jobs on the Swedish job market which last more than 10 days and have not been filled at the end of the month (Thomson). Intuitively, we expect an increase in vacancies to indicate a raise in firm expectations and thereby have a generally positive relationship toward increasing output and profits which in turn will raise stock returns.

4.2.7 Bankruptcies

Bankruptcy is the legal definition for when a firm or a person is unable to repay amassed debts. The entity is at the time of bankruptcy put under legal control and all available assets held by the bankruptcy estate are used to repay creditors. Firms file for bankruptcy all the time, but intuitively the number of bankruptcies should be higher during (and just prior to) ‘bad times’. During our full sample 1986-2012 there were 763,6 bankruptcies on average every month. If we compare that number to the average of 1498,8 bankruptcies per month for the period 1991-1994 (Thomson) which covers the period just before and after the financial crisis in Sweden in 1992, we see that there is a large difference. In other words, we expect the number of bankruptcies to give us information over business cycles (good/bad) and during periods of increasing bankruptcies we expect to see stock returns decrease, since rising bankruptcies intuitively indicate a harsher business climate.

4.2.8 Visible trade balance and Exports

Sweden is a small and open economy who largely depends on exports and imports. The visible trade balance refers to the physical goods part of the balance of trade, and disregards the effect from the trade of services. The VTB is thus the difference between exports and imports of physical goods, and have generally been running at a surplus (the value of the exports have been greater than the value of imports) in Sweden for the entire period 1986-2012 (Thomson). The visible trade balance can be considered in contrast to the invisible trade balance, which regards the balance of trade for services. We also used exports of goods and services as a potential variable, but the data series lack observations before 1990 (Thomson). In the extant literature Flannery and Protopapadakis (2002) found balance of trade to be one of the six strong candidates in their search for real macroeconomic variables that exhibit compelling evidence for having an impact on equity prices.

4.2.9 Difference Long and Short Interest Rate

The variable LRr_SRr is calculated as the difference between the long interest rate of the ten year SSVX and the short interest rate of the three month SSVX. The major determining factors for the difference between the long and short interest rates is the risk associated with inflation, since future inflation is unknown an investor will require a premium to hold the risk. This premium is thereby determined by market expectations on future inflation (Fregert and Jonung 2005). In the extant literature, Hyde and Kappel (2009), Ang and Bekaert (2001) and Rapach, Wohar and Rangvid (2005) all found interest rates to exhibit a relationship toward stock returns.

4.2.10 Money Stock

The central bank (Riksbanken) controls the supply of money in the economy and have the ability to create two types of monies. They can issue currency (coin, paper) or create bank reserves for commercial banks. The sum of these two is the monetary base, or M0, and is the most liquid of all money measurements. In todays society we generally see no difference between money in our hands or “money” on a card, which leads us into the second measurement we use for money, M1 or the monetary aggregate. M1 consists of the currency in circulation plus the current accounts or bank accounts that are payable on demand (Burda and Wyplosz 2009). In previous literature, money measures were found to have a positive influence on stock returns by both Asprem (1989) and Jiranykul (2009).

4.2.11 Composite Leading Indicators

The OECD Composite Leading Indicators (CLI) is a system of regional and country specific components designed to predict business cycles. The measure utilizes a growth cycle approach where deviations from the trend level of the GDP are meant to indicate future turning points in the economy. The Swedish CLI is composed of OECD regional components as well as country specific components that hold a relation toward the reference series (GDP) during peaks and trough’s in the economy. The country specific components for Sweden consist of measures for; the 5 year bond yield, new orders, overtime hours, order book level and AFGX’s share price index. To be able to provide qualitative information over business cycles, the CLI is computed for every month and each previous month is subject to revisions to better isolate cyclical patterns (OECD webpage 2013). In other words, when the CLI decreases we expect the economy to turn toward ‘bad times’ and generally perform worse than during the opposite case of increasing CLI.

4.2.12 Real Effective Exchange Rate

Nominal exchange rates are uninformative when used to compare prices of goods between two different countries. Since such a comparison would contain information for the different relative prices of money in the compared countries, and thereby would not contain information on the changes in real prices. It is for such comparisons that the real exchange rate exists (Burda and Wyplosz 2009). The real exchange rate takes the market exchange rates, as well as the changes in price levels, into consideration. Thereby it is possible to compare prices between countries, making the real exchange rate an indicator for international competitiveness. In other words, an increase in the real exchange rate between SEK and USD would entail that the same good in Sweden will have become more expensive, compared to its counterpart in the U.S., and Sweden will therefore be less attractive for U.S. buyers.

5. Empirical Results

5.1. Linear Regression Analysis

5.1.1. Transforming variables for non-stationarity

Appendix table 1.1. presents the results for 26 Augmented Dickey Fuller tests, which are performed to make sure that our variables are non-stationary. 8 of our of the 21 variables tested were found to show non-significant p-values, for the five percent confidence interval, for the null hypothesis that the variable has a unit root. The variables exhibiting unit root were bnkrptp unemp, vac, x, long10y, indprod, energycpi and CCISWE93. To correct for the non-stationarity, these eight variables were differentiated once, and the newly differentiated variables showed significant p-values under the 5 percent confidence, and we conclude that all variables now are stationary.

5.1.2. Simple Linear Regression Analysis

Using the GTS (general to specific) approach the model is narrowed down from the initial 12 lags until only one variable remain. However, this variable is found not-significant at the 10% level, having a p-value for the f-statistic of 10,7944 as seen in appendix table 2.1. We therefore are unable to confirm any significant impact on OMXS30 from its own lags. The regression has a low R^2 of 0,8%, which means that the model explains only 0,8% of the variation in the dependent variable. In appendix table 2.2 we present the results from our tests concerning the OLS assumptions. We found no evidence for either heteroskedasticity or autocorrelation, with p-values 0,2071 and 0,8558 respectively. We do however run into problems when performing the RAMSEY'S RESET test, where the observed p-value of 0,04 indicates that we either have missing significant variables, not included in the model, or that the OMXS30 exhibits a nonlinear trend. We acknowledge the issue, but do not pursue it since our original purpose is not to get a fully functional model, and since it is very likely that our simple linear regression model lacks some significant variables

5.1.3. Multivariate Linear Regression Analysis

The multivariate linear regression model is narrowed down, through the GTS approach, into five independent variables and presented in appendix table 3.1. The adjusted R^2-value is increased from 0,004 in the simple regression to 0,06 in the multivariate, which indicates that adding economic variables and more lags of OMXS30 gives an increased explanatory power over the variation in stock prices, compared to only using past prices. This conclusion might suffer from the fact that we are using monthly observation whereas stock prices tend to fluctuate heavily each day, implying that we might have yielded different results if we were to use daily observations instead. However, since we are primarily looking for long term relationships and we find that the multivariate regression model does indeed add some explanatory power, we proceed to the next step, and estimate forecast models using the methods from section 3.2. The multivariate regression shows no sign of heteroskedasticity, autocorrelation or non-linearity with p-values of 0,49, 0,70 and 0,72 respectively. The errors terms also seem normally distributed, and the results from all these tests on the multivariate linear regression model along with the final model are presented in appendix table 3.2.

5.2. Results Forecast Models

5.2.1 Joint F-test

To establish which of our economic variables that actually exhibit a correlated relationship towards our dependent variable OMXS30, we perform a joint f-tests of OMXS30 against each of the 19 independent variables using a fixed lag length of 12. We also test OMXS30 as an independent variable, using a fixed lag length of 12, and allowing each of our previously independent variables to act as the dependent variable. The results of the joint F-tests are summarized below in table 5.1.

Table 5.1 Results from joint-F-test

Lags of variable		Lags of variable	
Dependent variable:	**OMXS30**	**Independant variable:**	**OMXS30**
OMXS30	0,585393	**OMXS30**	0,585393
cpi	0,359249	**cpi**	0,800024
CCI	0,308475	**CCI**	0,259232
Oilexch	**0,014935**	**Oilexch**	**0,004362**
LRr_SRr	**0,048320**	**LRr_SRr**	0,240194
M1	**0,009867**	**M1**	0,904567
dInd prod	**0,047729**	**dInd prod**	0,913091
dunemp	0,256462	**dunemp**	0,106446
VTB	0,141385	**VTB**	0,947093
Gold	0,337002	**Gold**	0,908054
dX	0,135909	**dX**	**0,000000**
Prodtendancy	0,337002	**Prodtendancy**	0,908054
RExch	0,876380	**RExch**	0,833122
CLI	**0,000088**	**CLI**	**0,000000**
M0	**0,016374**	**M0**	0,467826
dCCISWE93	0,407711	**dCCISWE93**	0,000001
dVAC	0,290530	**dVAC**	0,125493
dbnkrptp	0,309987	**dbnkrptp**	0,536103
denergycpi	0,465210	**denergycpi**	0,386878

On the left hand side OMXS30 is the dependent variable, while it functions as the independent variable on the right hand side. By running regressions consisting of the dependent variable and its twelve lags, ranging from month one to month twelve, we gain the F-statistic given by each independent variables relation toward the dependent variable. The significant variables are underlined and we can see two variables, *CLI* and *OilExch,* which are significant both as independent and dependent variable in their relation toward OMXS30. This raises the question of causality. We perform a Granger-Causality test for each of the variables to see if *Oilexch* and *Cli* are useful in forecasting *OMXS30*. The results are presented in appendix table 4.1 and 4.2 in. The p-values of the tests indicates that the null hyphotesis, that *OilExch/CLI* does not granger-cause OMXS30, are rejected at the ten percent and 1 percent level with p-values of 0,0592 and 0,0010 respectively. In other words both variables seem to be useful for predicting OMXS30. Six of our independent variables thereby show significant p-values for the joint F-test, and these are the variables we use for estimating forecast models. Following Stock and Watson (2003), we will also include OMXS30 in all our regressions even though it might be insignificant.

We will thereby model every combination of our bivariate and trivariate models using the six different significant independent variables, from the joint F-test, and combine these variables with the OMXS30 for all regressions. For the univariate model, we will only use OMXS30 and its own lags. We also include the multivariate regression calculated using the GTS approach. This equals 23 model combinations. For the recursive approach, we will use all combinations and model each combination over all three forecast periods (one, three and six months) and for comparison we will also add a rolling window approach for the one month ahead forecast period. This gives a total of 92 different model specifications, which will be run over the whole and both sub samples, resulting in 276 forecasts in total. The results of all forecast models are presented in appendix A.5. and organized in such a way that the models are put in the same table as the benchmark model they are compared with. The tables are sorted by time period, forecast horizon used and whether the recursive or rolling window approach is used.

5.2.2. Results for bivariate models

The tables in appendix A.5., reports the summarized results for the different bivariate models that were tested. The results are limited, since they are almost at unity with the benchmark model, and none of our models show any significant indications of being able to outperform the benchmark model over all samples. The best bivariate model from the recursive approach, considering all time periods, is the *LRr-SRr.* At one month forecast horizons the model produce a relative MFSE value of 0,98 against the benchmark model indicating that it might be a better predictor than the benchmark model using recursive one month ahead forecasting. Over the three and six month horizon however, the MFSE values are larger than 1. The model also performs poorly with the rolling window approach and returns a Relative MFSE of 1,17. If we instead regard the early sub-sample (2003:01-2007:12) we find that *OilExch* seem to outperform the benchmark model over all three forecasting horizons for the recursive approach but also for the one month rolling window approach. The relative MFSE and relative RMSFE for *OilExch* are all below 1, with the lowest MFSE of 0,90 given by the rolling window approach with a one month forecast horizon. Results suggesting that our models perform better over certain time periods.

The early sub-sample exhibits lower standard deviations than the full sample, and with smaller variability, it is easier for the forecasts to predict. The difference between the results for the rolling and recursive approaches might also suggests that there is a difference between the two estimation approaches, when constructing predictive model. As previously mentioned, *OilExch* performs better using the rolling window approach but on average, the recursive approach produce lower MFSE values. The recursive window approach has an average MFSE value, over the full sample and with a one month forecasting horizons, of 0,00388 while the rolling window approach returns an MFSE of 0,00423.

5.2.3. Results for Trivariate Models

The trivariate models show a similar pattern as the ones observed for the bivariate models, returning limited results with most models performing close to unity compared with the benchmark model. The results from the trivariate models are presented in the tables in appendix A.5. Among the trivariate models, there is only one model that show any signs of being able to outperform the benchmark model. This is the trivariate m0, m1 model over the late sample period, using a six month ahead forecast horizon, and returning a relative MFSE of 0,82. The fact that the best performing trivariate model consists of m1 and m0, which represent almost the same underlying data, is disturbing and indicates that our forecasted results may be a case of luck and not significantly indicate good forecasting.

5.3 Economic Interpretation of Forecast Results

The results for our managed portfolios are presented in appendix chapters A.6 sorted by the three different time periods and the two portfolio strategies. For the economic interpretation we use the seven best performing forecast model previously estimated. These seven models consist of five bivariate, one trivariate and the multivariate linear regression model. The bivariate models used are: *Oil* 1 month recursive, *LRr_SRr* 1 month recursive, *m1* 3 month recursive, *LRr_SRr* 3 month recursive, *LRr_SRr* 6 month recursive. The trivariate model used is the *m1 m0* 6 month recursive model and the seventh model is the 1 month rolling window multivariate linear regression model. All models were then used with our two portfolio strategies (the switch and long/short) and tested over all three time periods, resulting in a total of 42 differently specified portfolios.

Given the forecasting period stretching over ten years time, and thereby containing a total of 120 monthly observations, a sufficiently large sample to make a robust comparison between the performance of the different portfolios. The switch strategy is generally superior, and returns a higher final net wealth than the comparable long/short strategies over all time periods. The average final net wealth over the full sample of the switch strategy is 13 906 SEK, while the same result for the long/short strategy is 12 868 SEK.

The p-values of the Jensen's Alpha and the Sharpe Ratio were calculated under the assumption of IID (identically individually distributed observations). All returned p-values from the Jensen's Alpha are above 0,95, which means we cannot reject the null hypothesis that the Alpha is equal to zero, thereby we cannot prove any excess returns for our portfolios using the Jensen's Alpha. However, we are able to reject the null hypothesis that the Sharpe Ratio is equal to zero in a number of cases. All these significant p-values are located in the early sample though, the same period that displayed the lowest standard deviation (or risk) of all periods, which gives a generally higher Sharpe Ratio and since we assume that the returns are IID, a higher Sharpe Ratio will result in a lower p-value. This also means that we find a lot of low and insignificant Sharpe values in the late sample, due to the high standard deviation (risk) associated with the late time period. The standard deviation of stock returns over the full sample is 0,059, and the standard deviation of the early sample is 0,046 while the late sample has a standard deviation of 0,14. This is expected, since the last period (2008-2012) has to deal with the financial crisis and its aftermath.

Table 5.2 Economic Results – The Two Best Performing Portfolios

The table presents the two best performing models observed. Both are managed using the switch strategy. The buy and hold strategy is included for comparison reason. The shaded grey areas represent points where the buy and hold are put into relative terms of itself, thereby not returning any information, and exempt from the model.

Sample	Full sample			Early sample			Late Sample		
Model	Buy and hold	Bi-oil-1m	bi-m1-3m	Buy and hold	Bi-oil-1m	bi-m1-3m	Buy and hold	Bi-oil-1m	bi-m1-3m
Net Wealth	13159,61	18653,05	**19203,53**	18057,88	**21612,67**	16782,97	7287,462	8630,606	**11407,12**
Wealth in relation to b/h		5493,439	**6043,92**		**3554,797**	-1274,9		1343,145	**4119,655**
Mean Return	0,004185	0,006098	**0,007946**	0,010984	**0,013443**	0,009518	-0,01709	-0,00125	**0,020737**
Std. Deviation	0,059635	**0,041464**	0,071093	0,046193	**0,032218**	0,040831	0,143155	**0,048165**	0,203352
Sharpe Yearly	0,243111	**0,50942**	0,387161	0,823689	**1,44541**	0,807498	-0,41349	-0,08976	**0,353263**
P-value	0,442582	**0,109092**	0,222273	0,06704	**0,000002**	0,011751	0,352912	0,776568	**0,265183**
Jensens Alpha		0,004089	**0,006154**		**0,007988**	0,001004		-4,3E-05	**0,021777**
Jensen P-value		0,964272	**0,94625**		**0,930273**	0,991228		0,999627	**0,811474**

The Portfolio that performed best over the full sample 2003:01-2012:12, in view of the final net wealth, was the bivariate *m1* three month ahead forecast model using the switch strategy. It outperformed the buy and hold strategy by 46% over the full sample period, resulting in a net wealth after incurred transaction costs of 19 204 SEK. It is worth noting that the portfolio in question performed 10% below the buy and hold during the early sample, and 57% above for the later sample, a pattern that seem to fit most of the portfolios we tested. In the early sample, the average net wealth in comparison to the buy and hold strategy, for all portfolios and strategies, was equal to -12% over the early sample and 16% for the late sample. Another intuitive result, since the stock market in the early sample exhibit a linear and continuous positive trend, for which the buy and hold strategy should perform rather well. Henceforth, the two management strategies seem rather inefficient over the early sample, but once the financial crisis hits, the market plummets and becomes more volatile, and an opportunity for our management strategies to outperform the buy and hold strategy appears.

The only model that outperforms the buy and hold strategy over all samples is the recursive bivariate *OilExch* one month ahead forecast using the switch strategy. We observe that even if the *Bi-m1-3m* results in a higher final net wealth, over the full sample, it carries a significantly higher risk (0,07) compared to the *bi-oil-1m* (0,04). The same conclusion can be drawn from the Sharpe Ratio, where *OilExch* display a ratio of 0,50 while *Bi-m1-3m* exhibits a ratio of 0,39. However, both portfolios demonstrated ratios are insignificant, with p-values of 0,11 and 0,22 respectively, and thus we cannot be sure whether the Sharpe Ratio is not equal to zero for both models. We can also see that during the late period, when *Bi-m1-3m* makes the biggest relative gain relative the buy and hold strategy, it carries a standard deviation of 0,20 which is a lot higher than the comparable value for *OilExch* of 0,048. However, once again we cannot comment on the Sharpe Ratios, since they are both insignificant. In conclusion, the *Bi-m1-3m* portfolio results in the highest final net wealth, but it also carries a larger risk than the portfolio for *OilExch,* which in results in a lower final net wealth. These results can be viewed in the light of the CAPM, where taking on more non-systematic risk in turn should be rewarded by higher returns.

6. Conclusions

Mainly following the approaches of Stock and Watson (2003) and Hyde and Kappel (2009), we use linear regression models to determine whether variables depicting economic factors can be used to predict future stock returns on the Swedish stock market.

The performance of the estimated forecast models are evaluated using a collection of standard metrics and through an economic interpretation, where we construct two different portfolio strategies that are examined over three different sample periods. Unfortunately we are unable to find evidence that supports the ability, of any of our models, to consistently forecast the returns of the stock market well over the different time periods. We do however find some models that indicate the possibility of being able to forecast the stock returns rather well over certain periods and methods. The bivariate LRr_SRr (difference between long and short interest rate) one-month ahead horizon forecast model exhibits the most promising results in the standard metrics tests, and the models outperform the benchmark model over the late and full sample. The bivariate *OilExch* one month ahead forecast model performs well in the early sample but rather badly in the late sample, indicating that the model might be a good predictor during economic booms while being a bad predictor during recessions. This relationship is further analyzed in graph 6.2 where the price indices of OilExch and OMXS30 are compared. It is evident that the two variables develop more similarly during the early sample (2003:01-2007:12) than in the later sample (2008:01-2012:12), where the oil prices continue to rise during the first seven months up until the financial crisis of 2008 while the stock index starts to fall at the beginning of 2008.

Overall our managed portfolios show rather modest returns compared to the simple buy and hold strategy. This is either due to the limitations of our simple management strategies or the fact that our models lack the necessary market timing needed to perform well i.e. models built around when the economic variables actually are publicized, and management strategies based on these publications where we would make portfolio decisions at the time of these news instead of updating our portfolios at predefined regular dates. Only two of our managed portfolios exhibit higher returns than the buy and hold strategy, for both the short/long and the switch strategy, over the full sample. The two portfolios are; the recursive bivariate *OilExch* model with a one-month forecast horizon and the recursive bivariate *m1* model with a three-month forecast horizon.

We are generally concerned that the performances of our managed portfolios are based largely on luck, and thereby not solely on well performing forecast models. As an example, the recursive bivariate *m1* model with a three-month forecast horizon was the best performing model in economic terms, generating a 46% larger final net wealth than the buy and hold strategy. However, the major part of this net wealth was accumulated during a drop of 25% in the stock index over a three-month period (2011:07-2011:09), but since a forecasted -1% triggered a switch for the same period, the strategy increased roughly 25% in net wealth in comparison to the buy and hold strategy. Considering this example, our results seem to indicate that we lack the necessary evidence to be able to disprove either the EMH or the random walk hypothesis, since it is impossible based on our results to determine whether the portfolio beats the buy and hold strategy thank to the underlying forecasts, or if we simply should turn our gratitude toward lady luck.

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Appendix A

A.1. Unit root test

Table.1.1 Results Augmented Dickey Fuller tests

Table 1.1 shows all p-value from the Augmented Dickey Fuller test using lags selected with Schwartz info criterion. The null hypothesis is that the variable have Unit root, all variables found with unit root at the 5% level is differentiated once and re-tested.

Table 1.1 unit root test with Augmented dickey fuller, trend and intercept

Variable	P-value	Diff 1	P-value
LRr-SRr	0,0468		
Short_term	0,4870		
Long10Y	0,1478	Dlong10y	0,0000
Unemp	0,5914	Dunemp	0,0081
Vac	0,0910	Dvac	0,0001
X	0,0360	DX	0,0000
Rexch	0,0000		
Prodtendancy	0,0000		
OMXS30	0,0000		
OilExch	0,0000		
M1_milj	0,0000		
M0	0,0018		
bnkrptp	0,4419	Dbnkrptp	0,0000
Indprod	0,6233	Dindprod	0,0000
Gold	0,0000		
Energy_cpi	0,2587	DenergyCpi	0,0000
CPI	0,0000		
CLI	0,0010		
CCI	0,0000		
CCISWE93	0,4533	DCCISWE93	0,0000
Vtb	0,6071	DVtb	0,0167

A.2. Simple linear regression

Table 2.1. Simple Linear Regression Model

The table show the results from the simple linear regression, or the AR(1), model for OMXS30.

Table 2.1, Dependent Variable: OMXS30					
Method: Least Squares		observations: 322 after adjustments			
Variable	Coefficient	Std. error		t-stat	P-value
C	0,004593	0,004137		1,110396	0,2677
OMXS30(-1)	0,089781	0,0555696		1,612017	0,1079
R^2	0,008055	F-stat	2,5986	Durbin-Watson	1,99
Adjusted R^2	0,004955	P-value f-stat	0,1079		

Table 2.2. Results from standard tests on the Simple Linear Regression Model

This table contain the results from a number of basic tests, used to test whether our model fulfill the six OLS assumptions.

Table 2.2 Tests for OLS	
Test	P-value
Breusch-Pagan (*heteroskedasticity*)	0,2071
Serial LM-test (*autocorrelation*)	0,761
Ramsey RESET test (*correctly specified model*)	0,042
Jarque-Bera (*normality*)	0,000

A.3. Multivariate linear regression

Table 3.1. Final Multivariate Linear Regression Model

The table show the results from the final Multivariate linear regression model using the GTS approach.

Table 3.1, Dependent Variable: OMXS30					
Method: Least Squares		observations: 322 after adjustments			
Variable	Coefficient	Std. error	t-stat	P-value	
C	0,005113	0,004148	1,23706	0,2186	
OilExch(-6)	0,091147	0,041431	2,19997	0,0286	
OilEcxh(-12)	-0,073780	0,0421244	-1,78884	0,0746	
Aunemp(-7)	2,960271	1,437886	2,058767	0,0352	
Aenergycpi(-12)	0,295283	0,139562	2,115778	0,0352	
M1_milj(-10)	0,337533	0,130897	-2,578776	0,0104	
R^2	0,076458	F-stat	5,0334	Durbin-Watson	1,85
Adjusted R^2	0,061268	P-value f-stat	0,00019		

Table 3.2. Results from standard tests on the Multivariate Linear Regression Model

The table contain the results from a number of basic tests, used to test whether the final multivariate model fulfill the six OLS assumptions.

Table 3.2 Tests for Multivariate regression	
Test:	p-value:
Breusch-Pagan (*heteroskedasticity*)	0,4918
Serial LM-test (*autocorrelation*)	0,4259
Ramsey RESET test (*correctly specified model*)	0,7259
Jarque-Bera (*normality*)	0,0000

A.4. Granger causality test

Table 4.1 Granger-Causality Test OMXS30 and OilExch

Table 4.1 and 4.2 presents two Granger-Causality test and to show if the variables are good predictors for OMXS30, in the first one, OilExch and OMXS30 are tried against each other and in the second one CLI and OMXS30 are tried. A low p-value indicates that the variable is a good predictor for the other.

Table 4.1 OMXS30 and OilExch, Pairwise Granger Causality Tests

Sample: 1986M02 2002M12	Obs: 191	
Null hypothesis:	F-Statistic	P-value
OILEXCH does not Granger Cause OMXS30	1,75728	**0,0592**
OMXS30 does not Granger Cause OILEXCH	1,01248	0,4397

Table 4.1 Granger-Causality Test OMXS30 and CLI

Table 4.2 OMXS30 and CLI, Pairwise Granger Causality Tests

Sample: 1986M02 2002M12	Obs: 191	
Null hypothesis:	F-Statistic	P-value
CLI does not Granger Cause OMXS30	2.9608	**0,0010**
OMXS30 does not Granger Cause CLI	2,84830	**0,0014**

A.5. Results from Forecast Models

A.5.1 Recursive 1 month ahead forecast results

Table 5.1.1 Forecast Results Recursive 1 Month Ahead, Full Sample

1 month full sample estimation 1987:01-2002:12 and out of sample forecast 2003:01 – 2012:12
all values are presented relative to the benchmark model OMSX30.

Table 5.1.1 Recursive window approach, Full sample, 1 month				
Ar benchmark model:	**OMXS30**			
Mfse:	0,003731		Mae:	0,043651
Rmsfe:	0,061085		Theil's U:	1,0041
		Bi-variate models		
Evaluation method:	Mfse	Rmsfe	MaE	Theil's U
Oilexch	1,048293	1,023868	1,041351	1,139926
Aindprod	1,045184	1,022346	1,049002	1,068818
m1	1,024468	1,012163	1,03292	1,16094
m0	1,072064	1,03541	1,044512	1,034957
Cli	1,071448	1,035115	1,105817	1,130067
LRr_SRr	0,986332	0,993141	1,00614	0,969117
		Tri-variate models		
Oilexch + M1	1,063703	1,031366	1,053584	1,294592
Oilexch + indprod	1,097309	1,04754	1,091384	1,178867
Oilexch + CLI	1,040307	1,019956	1,107122	1,383328
Oilexch + M0	1,116685	1,056741	1,092484	1,097301
M1 + inddprod	1,067696	1,033298	1,072049	1,239717
M1 + CLI	1,108351	1,052795	1,129711	1,250075
M1 + M0	1,093289	1,045609	1,064535	1,202171
Indprod + CLI	1,187865	1,087714	1,20499	1,138632
Indprod + M0	1,117891	1,057314	1,09088	1,14401
Cli + M0	1,16471	1,079217	1,169916	1,157255
LRr_SRr + Oilexch	1,018787	1,009364	1,044123	1,072204
LRr_SRr + M1	1,027362	1,013588	1,055417	1,116921
LRr_SRr + m0	1,070992	1,034886	1,06568	0,998207
LRr_SRr + INDPROD	1,034813	1,017271	1,065497	0,9999
LRr_SRr + CLI	1,106046	1,051682	1,138966	1,35863
		Multivariable linear regression		
oil(6,12)unemp(7)energy(12)m1(10)	1,072386	1,035557	1,057616	1,175481

Table 5.1.2 Forecast Results Recursive 1 Month Ahead, Early Sample

1 month sub-sample 2003:01-2007:12. Estimation between 1987:01-2002:12 and out of sample forecasted between 2003:01 – 2007:12 all values are presented relative to the benchmark model OMXS30.

Table 5.1.2 Recursive window approach sub-sample 2003:01-2007:12, 1 month				
Ar benchmark model	**OMXS30**			
Mfse:	0,002423		Mae:	0,037276
Rmsfe:	0,049223		Theil's U:	0,96401
Bivariate models				
Evaluation method:	Mfse	Rmsfe	MaE	Theil's U
Oilexch	0,920343	0,959308	0,974461	1,16617
Aindprod	1,124438	1,060378	1,06535	1,051649
m1	1,070948	1,034862	1,036297	1,169179
m0	1,124149	1,060256	1,049013	1,051649
Cli	1,141814	1,068566	1,07203	1,21005
LRr_SRr	1,036114	1,017898	1,012635	1,01529
Trivariate models				
Oilexch + M1	0,976351	0,988095	0,98047	1,325505
Oilexch + indprod	1,019109	1,009508	1,01792	1,220734
Oilexch + CLI	0,982211	0,991061	0,99831	1,456209
Oilexch + M0	1,066821	1,032871	1,056551	1,142001
M1 + inddprod	1,166825	1,080206	1,086892	1,17478
M1 + CLI	1,2646	1,124556	1,129923	1,360671
M1 + M0	1,170952	1,063048	1,428909	1,206834
Indprod + CLI	1,330637	1,153526	1,152189	1,180797
Indprod + M0	1,179	1,085814	1,096979	0,968797
Cli + M0	1,286764	1,134368	1,148541	1,212021
LRr_SRr + Oilexch	0,969252	0,984499	0,985809	1,134221
LRr_SRr + M1	1,141525	1,068423	1,072272	1,196253
LRr_SRr + m0	1,15498	1,07401	1,062936	1,031763
LRr_SRr + INDPROD	11,56383	1,075351	1,08987	1,033952
LRr_SRr + CLI	1,243634	1,11517	1,147441	1,190548
Multivariable linear regression				
oil(6,12)unemp(7)energy(12)m1(10)	1,152998	1,073787	1,069509	1,239406

Table 5.1.3 Forecast Results Recursive 1 Month Ahead, Late Sample

1 month sub-sample 2008:01-2012:12. Estimation between 1987:01-2002:12 and out of sample forecasted between 2008:01 – 20012:12 all values are presented relative to the benchmark model OMSX30.

Table 5.1.3 Recursive window approach, Sub sample 2008m01-2012m12, 1 month				
Ar benchmark model	**OMXS30**			
Mfse:	0,00504		Mae:	0,050026
Rmsfe:	0,070992		Theil's U:	1,979
		Bivariate models		
Evaluation Method:	Mfse	Rmsfe	MaE	Theil's U
Oilexch	1,109784	1,053471	1,091173	0,627792
Aindprod	1,007083	1,003536	1,036801	0,675493
m1	1,002143	1,001071	1,030404	0,707428
m0	1,047025	1,023242	1,041179	0,565235
Cli	1,0376	1,018636	1,130992	0,53047
LRr_SRr	0,9624	0,981026	1,001299	0,466139
		Trivariate models		
Oilexch + M1	1,105716	1,051541	1,108084	0,736786
Oilexch + indprod	1,134923	1,065331	1,146124	0,582971
Oilexch + CLI	1,068235	1,033553	1,188222	0,732693
Oilexch + M0	1,140658	1,068022	1,119258	0,499495
M1 + inddprod	1,02004	1,009973	1,060988	0,896109
M1 + CLI	1,033235	1,016495	1,120817	0,511824
M1 + M0	1,055953	1,027609	1,059769	0,727135
Indprod + CLI	1,119229	1,063648	1,228081	0,508893
Indprod + M0	1,088514	1,043329	1,084336	1,001213
Cli + M0	1,106054	1,051696	1,185823	0,593482
LRr_SRr + Oilexch	1,04262	1,021087	1,087594	0,472036
LRr_SRr + M1	0,97246	0,986139	1,042858	0,478075
LRr_SRr + m0	1,03131	1,015537	1,067725	0,503911
LRr_SRr + INDPROD	0,976369	0,988125	1,047335	0,502532
LRr_SRr + CLI	1,039902	1,019763	1,132651	1,174785
		Multivariable linear regression		
oil(6,12)unemp(7)energy(12)m1(10)	1,033632	1,016678	1,048775	0,57807

A.5.2 Recursive 3 month

Table 5.2.1 Forecast Results Recursive 3 Month Ahead, Full Sample

3 month full sample estimation 1987:01-2002:12 and out of sample forecasted between 2003:01 – 2012:12 all values are presented relative to the benchmark model OMXS30

Table 5.2.1 Recursive window approach, Full sample, 3 month				
Ar benchmark model	**OMXS30**			
Mfse:	0,003372		Mae:	0,043034
Rmsfe:	0,060984		Theil's U:	1,0127
		Bivariate models		
Evaluation Method:	Mfse	Rmsfe	MaE	Theil's U
Oilexch	1,175269	1,032254	1,061393	1,169053
Aindprod	1,147747	1,020104	1,053678	1,068233
m1	1,127492	1,011068	1,036715	1,152266
m0	1,182446	1,035403	1,054608	1,03071
Cli	1,183691	1,03596	1,122973	1,107041
LRr_SRr	1,084282	0,99149	1,012293	0,967522
		Trivariate models		
Oilexch + M1	1,189593	1,038535	1,070897	1,332873
Oilexch + indprod	1,219872	1,051669	1,106939	1,191666
Oilexch + CLI	1,128678	1,003035	1,116141	1,351042
Oilexch + M0	1,243301	1,061721	1,106962	1,08028
M1 + inddprod	11,71354	1,030549	1,077079	1,240841
M1 + CLI	1,209196	1,047062	1,140377	1,225536
M1 + M0	1,200091	1,04311	1,072571	1,194332
Indprod + CLI	1,297781	1,0803	1,208858	1,109805
Indprod + M0	1,258486	1,068346	1,113236	1,179421
Cli + M0	1,267323	1,071921	1,171028	1,110102
LRr_SRr + Oilexch	1,132177	1,013167	1,053028	1,062506
LRr_SRr + M1	1,121442	1,008346	1,061835	1,1024
LRr_SRr + m0	1,174527	1,031943	1,07601	0,990125
LRr_SRr + INDPROD	1,134016	1,013987	1,073314	0,991607
LRr_SRr + CLI	0,794624	1,046225	1,148534	1,291695
		Multivariable Linear regression		
oil(6,12)unemp(7)energy(12)m1(10)	1,199142	1,0427	1,079123	1,166979

Table 5.2.2 Forecast Results Recursive 3 Month Ahead, Early Sample

3 month sub-sample 2003:01-2007:12. Estimation between 1987:01-2002:12 and out of sample forecasted between 2003:01 – 2007:12 all values are presented relative to the benchmark model OMXS30

Table 5.2.2 Recursive window approach sub-sample 2003:01-2007:12, 3 month				
Ar benchmark model	**OMXS30**			
Mfse:	0,002368		Mae:	0,036336
Rmsfe:	0,048664		Theil's U:	0,96382
		Bivariate models		
Evaluation Method:	Mfse	Rmsfe	MaE	Theil's U
Oilexch	0,919644	0,958964	0,978396	1,158826
Aindprod	1,110717	1,053921	1,063793	1,044178
m1	1,075965	1,037297	1,049455	1,157581
m0	1,113715	1,055339	1,060243	1,048951
Cli	1,159953	1,077018	10,95663	1,200639
LRr_SRr	1,034752	1,017241	1,029613	1,023147
		Trivariate models		
Oilexch + M1	0,977493	0,988698	0,979194	1,314146
Oilexch + indprod	1,009754	1,00487	1,020943	1,196281
Oilexch + CLI	0,999367	0,999671	1,02587	1,436575
Oilexch + M0	1,070687	1,034913	1,06938	1,128323
M1 + inddprod	1,156237	1,073442	1,088672	1,164118
M1 + CLI	1,281817	1,132192	1,161933	1,346724
M1 + M0	1,15573	1,075045	1,079508	1,195348
Indprod + CLI	1,322819	1,150152	1,161107	1,169617
Indprod + M0	1,177139	1,08495	1,109038	0,969611
Cli + M0	1,276201	1,129685	1,152989	1,186217
LRr_SRr + Oilexch	0,960983	0,980293	0,986185	1,136312
LRr_SRr + M1	1,59674	1,263624	1,257568	1,158308
LRr_SRr + m0	1,137615	1,0666	1,080939	1,029176
LRr_SRr + INDPROD	1,147116	1,071038	1,100996	1,032703
LRr_SRr + CLI	1,241618	1,114294	1,159979	1,166815
		Multi-variable regression		
oil(6,12)unemp(7)energy(12)m1(10)	1,780297	1,334272	1,272897	1,231765

Table 5.2.3 Forecast Results Recursive 3 Month Ahead, Late Sample

3 month sub-sample 2008:01-2012:12. Estimation between 1987:01-2002:12 and out of sample forecasted 2008:01 – 20012:12 all values are presented relative to the benchmark model OMXS30

Table 5.2.3 Recursive window approach sub-sample 2008:01-20012:12, 3 month				
Ar benchmark model	**OMXS30**			
Mfse:	0,00507		Mae:	0,048528
Rmsfe:	0,071204		Theil's U:	1,2461
		Bivariate models		
Evaluation Method:	Mfse	Rmsfe	MaE	Theil's U
Oilexch	1,13373	1,064758	1,149872	1,210416
Aindprod	1,00785	1,003904	1,072226	1,137629
m1	0,99716	0,998567	1,052877	1,16034
m0	1,052605	1,025954	1,076554	0,930343
Cli	1,032683	1,016193	1,171303	0,819276
LRr_SRr	0,958914	0,979229	1,024439	0,736803
		TrIvariate models		
Oilexch + M1	1,125762	1,061008	1,166152	1,431827
Oilexch + indprod	1,150969	1,072819	1,198792	1,14413
Oilexch + CLI	1,034498	1,017092	1,211445	1,144049
Oilexch + M0	1,153514	1,073999	1,162339	0,804109
M1 + inddprod	1,017989	1,008946	1,095141	1,493781
M1 + CLI	1,009685	1,004831	1,152551	0,809967
M1 + M0	1,056471	1,027836	1,093987	1,198941
Indprod + CLI	1,108345	1,052764	1,26292	0,850895
Indprod + M0	1,124144	1,060249	1,143999	1,736538
Cli + M0	1,089627	1,043846	1,213588	0,872161
LRr_SRr + Oilexch	1,057102	1,028144	1,129224	0,716419
LRr_SRr + M1	0,960236	0,979903	1,065385	0,760268
LRr_SRr + m0	1,030928	1,015336	1,099015	0,80443
LRr_SRr + INDPROD	0,972603	0,986195	1,078161	0,802247
LRr_SRr + CLI	1,025878	1,01285	1,168439	1,737581
		Multivariable linear regression		
oil(6,12)unemp(7)energy(12)m1(10)	1,052545	1,025926	1,093307	0,92641

A.5.3 Recursive 6 month

Table 5.3.1 Forecast Results Recursive 6 Month Ahead, Full Sample

6 month full sample estimation 1987:01-2002:12 and out of sample forecasted between 2003:01 – 2012:12 all values are presented relative to the benchmark model OMXS30

Table 5.3.1 Recursive window approach, Full sample, 6 month				
Ar benchmark model	**OMXS30**			
Mfse:	0,003725		Mae:	0,042438
Rmsfe:	0,061032		Theil's U:	0,9926
		Bivariate models		
Evaluation Method:	Mfse	Rmsfe	MaE	Theil's U
Oilexch	1,083329	1,040847	1,090438	1,208543
Aindprod	1,059383	1,02928	1,072199	1,203204
m1	1,034604	1,017171	1,052477	1,174491
m0	1,114255	1,055594	1,067015	1,095507
Cli	1,082792	1,040585	1,136717	1,179025
LRr_SRr	1,001369	1,000688	1,027876	1,007455
		Trivariate models		
Oilexch + M1	1,106201	1,051776	1,111433	1,435724
Oilexch + indprod	1,137664	1,066621	1,156652	1,258714
Oilexch + CLI	1,032483	1,016123	1,117301	1,441668
Oilexch + M0	1,163919	1,0814	1,150738	1,138928
M1 + inddprod	1,083678	1,041011	1,105943	1,283699
M1 + CLI	1,102631	1,050072	1,146755	1,289643
M1 + M0	1,137289	1,066457	1,095268	1,30274
Indprod + CLI	11,93799	1,088101	1,214902	1,180234
Indprod + M0	1,181047	1,086774	1,130308	1,313621
Cli + M0	1,16306	1,078467	1,175668	1,188092
LRr_SRr + Oilexch	1,057933	1,028575	1,092865	1,104171
LRr_SRr + M1	1,034255	1,017007	1,079999	1,147491
LRr_SRr + m0	1,107221	1,052268	1,095127	1,056619
LRr_SRr + INDPROD	1,058309	1,028755	1,090744	1,032944
LRr_SRr + CLI	1,103463	1,050465	1,14487	1,325307
		Multivariable linear regression		
oil(6,12)unemp(7)energy(12)m1(10)	1,10545	1,051416	1,102526	1,190711

Table 5.3.2 Forecast Results Recursive 6 Month Ahead, Early Sample

6 month sub-sample 2003:01-2007:12. Estimation between 1987:01-2002:12 and out of sample forecasted between 2003:01 – 2007:12 all values are presented relative to the benchmark model OMXS30

Table 5.3.2 Recursive window approach sub-sample 2003:01-2007:12, 6 month				
Ar benchmark model	**OMXS30**			
Mfse:	0,002396		Mae:	0,035996
Rmsfe:	0,048946		Theil's U:	0,96233
Bi-variate models				
Evaluation Method:	Mfse	Rmsfe	MaE	Theil's U
Oilexch	0,968069	0,983921	1,035671	1,159685
Aindprod	1,138033	1,271115	1,101928	1,039664
m1	1,082102	1,040269	1,066257	1,161348
m0	1,180483	1,086524	1,086121	1,049432
Cli	1,218591	1,084849	1,114457	1,241674
LRr_SRr	1,06215	1,030626	1,033393	1,032089
Tri-variate models				
Oilexch + M1	1,036188	1,017938	1,044838	1,337483
Oilexch + indprod	1,087612	1,042904	1,113513	1,196367
Oilexch + CLI	1,071166	1,034998	1,055867	1,493459
Oilexch + M0	1,158569	1,07639	1,157712	1,116041
M1 + inddprod	1,177519	1,085339	1,130515	1,169453
M1 + CLI	1,306203	1,142913	1,17577	1,392765
M1 + M0	1,225436	1,107016	1,112235	1,21289
Indprod + CLI	1,395317	1,181261	1,189327	1,215799
Indprod + M0	1,225019	1,106832	1,136376	0,962456
Cli + M0	1,370774	1,170821	1,196411	1,252793
LRr_SRr + Oilexch	1,040362	1,020002	1,053534	1,142539
LRr_SRr + M1	1,608064	1,268132	1,27328	1,183586
LRr_SRr + m0	1,209283	1,099702	1,11404	1,031954
LRr_SRr + INDPROD	1,194841	1,093103	1,131015	1,036505
LRr_SRr + CLI	1,281534	1,132084	1,166185	1,208421
Multivariable linear regression				
oil(6,12)unemp(7)energy(12)m1(10)	1,054637	1,026968	1,051728	1,242401

Table 5.3.3 Forecast Results Recursive 6 Month Ahead, Late Sample

3 month sub-sample 2008:01-2012:12. Estimation between 1987:01-2002:12 and out of sample forecasted between 2008:01 – 20012:12 all values are presented relative to the benchmark model OMXS30

Table 5.3.3 Recursive window approach sub-sample 2008:01-20012:12, 6 month				
Ar benchmark model	**OMXS30**			
Mfse:	0,005054		Mae:	0,048879
Rmsfe:	0,071093		Theil's U:	1,1199
		Bivariate models		
Evaluation Method:	Mfse	Rmsfe	MaE	Theil's U
Oilexch	1,137964	1,066758	1,130813	1,419055
Aindprod	1,02212	1,011	1,050349	1,224752
m1	1,012089	1,006034	1,042349	1,271096
m0	1,082882	1,040609	1,052988	1,244308
Cli	1,038206	1,018919	1,153154	1,024109
LRr_SRr	0,972538	0,703909	1,023814	0,889883
		Trivariate models		
Oilexch + M1	1,139389	1,067419	1,160498	1,861684
Oilexch + indprod	1,161391	1,077673	1,188445	1,488704
Oilexch + CLI	1,014147	1,007047	1,162585	1,387535
Oilexch + M0	1,174548	1,083764	1,145625	1,156889
M1 + inddprod	1,039017	1,019313	1,08785	1,721582
M1 + CLI	1,006114	1,000535	1,125412	0,921422
M1 + M0	0,864192	0,929613	0,95763	1,049201
Indprod + CLI	1,098275	1,062045	1,218601	0,993392
Indprod + M0	1,160203	1,077124	1,125841	2,310117
Cli + M0	1,06462	1,031803	1,160396	0,982231
LRr_SRr + Oilexch	1,066282	1,032605	1,121872	0,896687
LRr_SRr + M1	0,977583	0,988733	1,059883	0,96589
LRr_SRr + m0	1,058842	1,029004	1,081221	1,120368
LRr_SRr + INDPROD	0,99357	0,996779	1,06111	0,989999
LRr_SRr + CLI	1,019034	1,009466	1,129176	1,847844
		Multivariable linear regression		
oil(6,12)unemp(7)energy(12)m1(10)	1,10051	1,049048	1,111725	1,030985

A.5.4. Rolling 1 month

Table 5.4.1 Forecast Results Rolling 1 Month Ahead, Full Sample

1 month full sample estimation 1987:01-2002:12 and out of sample forecast 2003:01 – 2012:12
all values are presented relative to the benchmark model OMXS30

Table 5.4.1 Rolling window approach, Full sample, 1 month				
Ar benchmark model	**OMXS30**			
Mfse:	0,003777		Mae:	0,043626
Rmsfe:	0,061458		Theil's U:	0,904705
		Bivariate models		
Evaluation Method:	Mfse	Rmsfe	MaE	Theil's U
Oilexch	1,087593	1,042877	1,07886	1,325426
Aindprod	1,13028	1,063146	1,119906	1,400894
m1	1,087417	1,042793	1,06811	1,365526
m0	1,102389	1,049947	1,063908	1,10372
Cli	1,138381	1,066949	1,134546	1,054695
LRr_SRr	1,178021	1,085367	1,102992	2,260747
		Trivariate models		
Oilexch + M1	1,153671	1,074091	1,142106	1,774788
Oilexch + indprod	1,221208	1,105083	1,212464	1,969939
Oilexch + CLI	1,192234	1,091895	1,191336	2,246225
Oilexch + M0	1,208071	1,099123	1,174252	1,455782
M1 + inddprod	1,208641	1,099382	1,146891	1,796321
M1 + CLI	1,280326	1,131515	1,169616	1,970239
M1 + M0	1,139755	1,067593	1,091497	1,458505
Indprod + CLI	1,295635	1,138259	1,202564	2,088518
Indprod + M0	1,216345	1,10288	1,12101	1,352673
Cli + M0	1,226584	1,107513	1,181597	1,696713
LRr_SRr + Oilexch	1,454108	1,205864	1,200034	1,205937
LRr_SRr + M1	1,291456	1,136423	1,163743	3,045413
LRr_SRr + m0	1,249067	1,117617	1,137099	1,760546
LRr_SRr + INDPROD	1,222739	1,105775	1,135765	1,868003
LRr_SRr + CLI	1,325083	1,151122	1,20552	6,382032
		Multivariable linear regression		
oil(6,12)unemp(7)energy(12)m1(10)	1,037389	1,018523	1,03964	1,509251

Table 5.4.2 Forecast Results Rolling 1 Month Ahead, Early Sample

1month full sample estimation 1987:01-2002:12 and out of sample forecast 2003:01 – 2007:12
all values are presented relative to the benchmark model OMXS30

Table 5.4.2 Rolling window approach sub-sample 2003:01-2007:12, 1 month				
Ar benchmark model	**OMXS30**			
Mfse:	0,002384		Mae:	0,036853
Rmsfe:	0,048827		Theil's U:	0,927343
		Bivariate models		
Evaluation Method:	Mfse	Rmsfe	MaE	Theil's U
Oilexch	0,903293	0,950417	0,955855	1,577725
Aindprod	1,434668	1,197776	1,218345	1,720601
m1	1,131072	1,063519	1,070418	1,626077
m0	1,238387	1,112828	1,074557	1,287841
Cli	1,110105	1,053615	1,030177	1,853976
LRr_SRr	1,036727	1,018198	1,071329	1,272001
		Trivariate models		
Oilexch + M1	1,036727	1,018198	1,041825	2,141485
Oilexch + indprod	1,292759	1,136996	1,19918	2,267795
Oilexch + CLI	1,009789	1,004883	1,00566	2,834456
Oilexch + M0	1,150149	1,07245	1,08004	1,491162
M1 + inddprod	1,42968	1,195692	1,207981	2,024502
M1 + CLI	1,504831	1,226716	1,186259	1,16126
M1 + M0	1,23351	1,110635	1,087354	1,588782
Indprod + CLI	1,434922	1,197882	1,210922	1,196551
Indprod + M0	1,282508	1,132478	1,110218	1,360369
Cli + M0	1,377006	1,173459	1,136292	1,684743
LRr_SRr + Oilexch	1,323042	1,150236	1,112069	1,160931
LRr_SRr + M1	1,097339	1,047539	1,039349	1,579569
LRr_SRr + m0	1,189311	1,090555	1,088157	1,011583
LRr_SRr + INDPROD	1,19236	1,091952	1,083633	1,109317
LRr_SRr + CLI	1,490582	1,220894	1,180194	1,635515
		Multivariable linear regression		
oil(6,12)unemp(7)energy(12)m1(10)	1,147557	1,071241	1,065193	1,618074

Table 5.4.3 Forecast Results Rolling 1 Month Ahead, Late Sample

1 month full sample estimation 1987:01-2002:12 and out of sample forecast 2008:01 – 2012:12
all values are presented relative to the benchmark model OMXS30

Table 5.4.3 Rolling window approach sub-sample 2008:01-20012:12, 1 month				
Ar benchmark model	**OMXS30**			
Mfse:	0,00517		Mae:	0,0504
Rmsfe:	0,071903		Theil's U:	0,806659
		Bivariate models		
Evaluation Method:	Mfse	Rmsfe	MaE	Theil's U
Oilexch	1,17258	1,082857	1,168803	1,27042
Aindprod	0,989917	0,994946	1,047928	1,119047
m1	1,067287	1,033096	1,066423	1,306245
m0	1,039676	1,019645	1,056121	1,167473
Cli	1,15142	1,073042	1,210861	2,090168
termspread	1,167434	1,080478	1,107905	10,42609
		Trivariate models		
Oilexch + M1	1,207597	1,098907	1,215431	1,579416
Oilexch + indprod	1,188214	1,090052	1,222178	2,213486
Oilexch + CLI	1,276365	1,129763	1,327103	1,475433
Oilexch + M0	1,234781	1,111207	1,243139	2,414894
M1 + inddprod	1,106713	1,052004	1,102221	1,356113
M1 + CLI	1,176799	1,084804	1,157447	5,954882
M1 + M0	1,096521	1,047149	1,094526	1,333013
Indprod + CLI	1,231405	1,109687	1,196452	6,457551
Indprod + M0	1,185836	1,088961	1,128902	1,713414
Cli + M0	1,15722	1,075742	1,214724	2,240402
LRr_SRr + Oilexch	1,489744	1,220551	1,244554	3,199009
LRr_SRr + M1	1,358367	1,16549	1,235231	14,70067
LRr_SRr + m0	1,258964	1,122036	1,164103	8,016552
LRr_SRr + INDPROD	1,218143	1,103695	1,162103	8,329473
LRr_SRr + CLI	1,230011	1,109059	1,211541	39,00842
		Multivariable linear regression		
oil(6,12)unemp(7)energy(12)m1(10)	0,977767	0,988821	1,007974	1,375256

A.6. Results from managed Portfolios

A.6.1. Long short strategy

Table 6.1.1 Results Long/Short Strategy. Full Sample

Table 6.1.1 summarizes all portfolios managed after the long/short strategy over the full sample (2003:01-20012:12).Bi- stands for bivariate, tri- stands for trivariate.Rec stands for recursive window and roll for rolling window. 1/3/6m is the forecast horizon and the variable name is the variable used in the model (not mentioning OMXS30 since it is included in all models). The third row wealth in relation to b/h is the net wealth compared of the model compared to the buy and hold

Table 6.1.1 Full sample Long/short strategy

	Buy and hold(b/h)	Multiple Roll 1m	Bi-oil Rec 1m	bi-term Rec 1m	bi-m1 Rec 3m	bi-term Rec 3m	Tri-m1m0 Rec 6m	Bi-term Rec 6m	Average
Net Wealth	13159,61	12732,88	16256,24	10828,08	18159,28	11619,67	12258,2	8221,976	12868,05
Wealth in relation to b/h	x	-1310,24	3096,634	-2331,53	4999,673	-1539,93	-901,405	-4937,63	-417,777
Mean Return	0,004185	0,002818	0,004952	0,001506	0,005906	0,002698	0,003403	-1,7E-05	0,003038
Std. Deviation	0,059635	0,039964	0,041639	0,040683	0,042549	0,051638	0,056272	0,054684	0,046776
Sharpe Yearly	0,243111	0,244232	0,412	0,128264	0,480835	0,181024	0,209464	-0,0011	0,236388
Sharpe P-value	0,442582	0,440487	0,194193	0,685135	0,130213	0,567283	0,508112	0,997226	0,503236
Jensens Alpha	6,94E-18	0,000947	0,002905	-0,00043	0,003765	-0,00043	-0,00032	-0,00348	0,000421
Jensen P-value	1	0,991726	0,974612	0,996253	0,967106	0,996202	0,997188	0,969559	0,984664

Table 6.1.2 Results Long/Short Strategy. Early Sample

Table 6.1.2 summarizes all portfolios managed after the long/short strategy over the early sample (2003:01-2007:12).Bi- stands for bivariate, tri- stands for trivariate.Rec stands for recursive window and roll for rolling window. 1/3/6m is the forecast horizon and the variable name is the variable used in the model not mentioning OMXS30 since it is included in all models. The third row wealth in relation to b/h is the net wealth compared of the model compared to the buy and hold

Table 6.1.2 Early sample Long/short strategy

	Buy and hold(b/h)	Multiple Roll 1m	Bi-oil Rec 1m	bi-term Rec 1m	bi-m1 Rec 3m	bi-term Rec 3m	Tri-m1m0 Rec 6m	Bi-term Rec 6m	Average
Net Wealth	18057,9	12642,4	19980,9	11121,1	16292,9	14810,5	18057,9	13842,7	15249,8
Wealth in relation to b/h	x	-5357,6	1923	-6936,8	-1765	-3247,3	0	-4215,1	-2799,8
Mean Return	0,010984	0,00451	0,012135	0,002614	0,009025	0,00727	0,010984	0,00642	0,00756
Std. Deviation	0,046193	0,03413	0,032761	0,040461	0,040962	0,03726	0,046193	0,0441	0,03941
Sharpe Yearly	0,823689	0,1311	1,283169	0,223806	0,763199	0,67656	0,823689	0,5046	0,62944
Sharpe P-value	0,06704	0,30391	0,005132	0,614211	0,08909	0,13077	0,06704	0,2577	0,2097
Jensens Alpha	-1,7E-18	-0,00135	0,006522	-0,00559	0,000533	0,00029	-6,9E-18	-0,0034	-0,00043
Jensen P-value	1	0,98821	0,943041	0,951182	0,995343	0,99738	1	0,9699	0,9778

Table 6.1.3 Results Long/Short Strategy. Late Sample

Table 6.1.3 summarizes all portfolios managed after the long/short strategy over the late sample (2008:01-20012:12).Bi- stands for bivariate, tri- stands for trivariate.Rec stands for recursive window and roll for rolling window. 1/3/6m is the forecast horizon and the variable name is the variable used in the model not mentioning OMXS30 since it is included in all models. The third row wealth in relation to b/h is the net wealth compared of the model compared to the buy and hold

Table 6.1.3 Late sample Long/short strategy

	Buy and hold(b/h)	Multiple Roll 1m	Bi-oil Rec 1m	bi-term Rec 1m	bi-m1 Rec 3m	bi-term Rec 3m	Trim1m0 Rec 6m	Bi-term Rec 6m	Average
Net Wealth	7287,462	10071,59	7498,907	9736,512	11145,53	7845,562	6788,286	5939,565	8432,279
Wealth in relation to b/h	x	2771,593	211,445	2449,051	3858,068	558,1003	-499,175	-1347,9	1143,026
Mean Return	-0,01709	0,001123	-0,00324	0,000399	0,002874	-0,00188	-0,00418	-0,0065	-0,00163
Std. Deviation	0,143155	0,044687	0,054416	0,040869	0,045739	0,062297	0,063773	0,06216	0,05342
Sharpe Yearly	-0,41349	0,087034	-0,20635	0,033783	0,217643	-0,10463	-0,22698	-0,36202	-0,08022
Sharpe P-value	0,352912	0,844455	0,642057	0,939287	0,623979	0,813542	0,609211	0,415648	0,698311
Jensens Alpha	-0,0136	0,002203	-0,00181	0,001301	0,003946	0,000206	-0,00199	-0,00441	-7,8E-05
Jensen P-value	0,881615	0,980745	0,984188	0,98863	0,965524	0,9982	0,982622	0,961513	0,980203

A.6.2 Switch strategy

Table 6.2.1 Results Switch Strategy. Full Sample

Table 6.2.1 summarizes all portfolios managed after the long/short strategy over the full sample (2003:01-20012:12).Bi- stands for bivariate, tri- stands for trivariate.Rec stands for recursive window and roll for rolling window. 1/3/6m is the forecast horizon and the variable name is the variable used in the model not mentioning OMXS30 since it is included in all models. The third row wealth in relation to b/h is the net wealth compared of the model compared to the buy and hold

Table 6.2.1 Full sample Switch strategy

	Buy and hold(b/h)	Multiple Roll 1m	Bi-oil Rec 1m	bi-term Rec 1m	bi-m1 Rec 3m	bi-term Rec 3m	Trim1m0 Rec 6m	Bi-term Rec 6m	Average
Net Wealth	13159,6	14243	18653	12268	19203,5	12459,6	12297,6	8214,8	13906
Wealth in relation to b/h	x	1083,6	5493,4	-891,3	6043,92	-700,06	-862,026	-4944,79	746,1
Mean Return	0,004185	0,0038	0,0061	0,0025	0,007946	0,00328	0,003429	-4,3E-05	0,0039
Std. Deviation	0,059635	0,03999	0,0415	0,0406	0,071093	0,051607	0,05627	0,054333	0,0507
Sharpe Yearly	0,243111	0,3259	0,5094	0,2172	0,387161	0,22018	0,211116	-0,00277	0,2669
Sharpe P-value	0,442582	0,3038	0,1091	0,4926	0,222273	0,486699	0,50478	0,993002	0,4446
Jensens Alpha	6,94E-18	0,0019	0,0041	0,0006	0,006154	0,00015	-0,00029	-0,00351	0,0013
Jensen P-value	1	0,98836	0,9643	0,9944	0,94625	0,998691	0,997423	0,997197	0,9831

Table 6.2.2 Results Switch Strategy. Early Sample

Table 6.2.2.summarizes all portfolios managed after the long/short strategy over the early sample (2003:01-2007:12).Bi- stands for bivariate, tri- stands for trivariate.Rec stands for recursive window and roll for rolling window. 1/3/6m is the forecast horizon and the variable name is the variable used in the model not mentioning OMXS30 since it is included in all models. The third row wealth in relation to b/h is the net wealth compared of the model compared to the buy and hold

Table 6.2.2 Early sample Switch strategy

	Buy and hold(b/h)	Multiple Roll 1m	Bi-oil Rec 1m	bi-term Rec 1m	bi-m1 Rec 3m	bi-term Rec 3m	Trim1m0 Rec 6m	Bi-term Rec 6m	Average
Net Wealth	18058	13499	21613	11509	16783	15647,6	18057,9	14271,2	15911
Wealth in relation to b/h	x	-4559	3554,8	-6549	-1274,9	-2410,31	0	-3786,71	-2146
Mean Return	0,010984	0,0056	0,0134	0,0032	0,009518	0,008195	0,0098	0,00694	0,0081
Std. Deviation	0,046193	0,0342	0,0322	0,0404	0,040831	0,037084	0,04728	0,044048	0,0394
Sharpe Yearly	0,823689	0,5672	1,4454	0,2731	0,807498	0,765551	0,717593	0,545385	0,7317
Sharpe P-value	0,06704	0,0748	0,000001	0,3886	0,011751	0,016763	0,024751	0,086516	0,0862
Jensens Alpha	-1,7E-18	-0,00003	0,008	-0,005	0,001004	0,001257	0,009178	-0,00296	0,0016
Jensen P-value	1	0,9972	0,93303	0,9559	0,991228	0,989013	0,919921	0,974126	0,9654

Table 6.2.3 Results Switch Strategy. Late Sample

Table 6.2.3 summarizes all portfolios managed after the long/short strategy over the full sample (2003:01-20012:12).Bi- stands for bivariate, tri- stands for trivariate. Rec stands for recursive window and roll for rolling window. 1/3/6m is the forecast horizon and the variable name is the variable used in the model not mentioning OMXS30 since it is included in all models. The third row wealth in relation to b/h is the net wealth compared of the model compared to the buy and hold

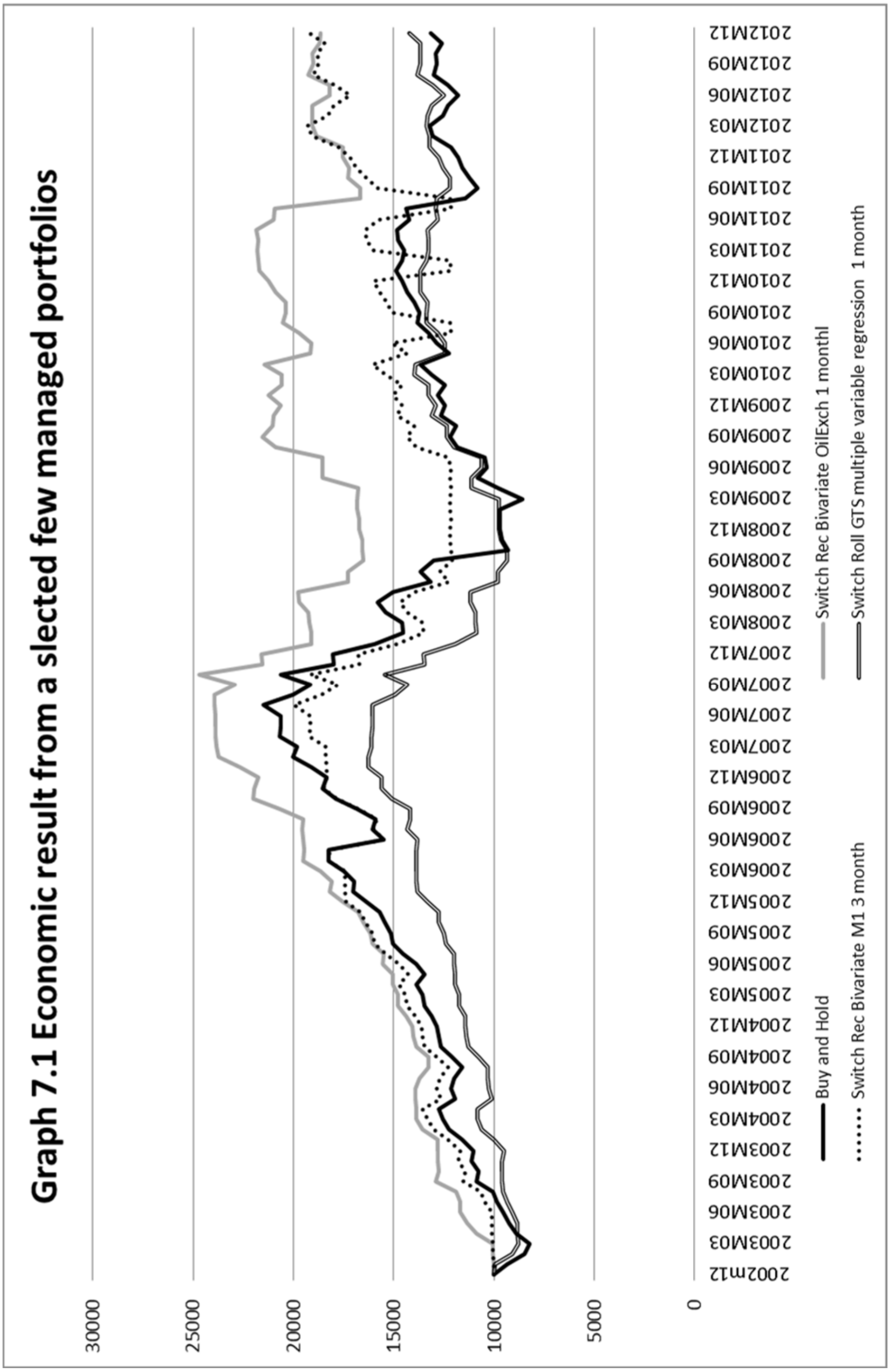
Table 6.2.3 Late sample Switch strategy

	Buy and hold(b/h)	Multiple Roll 1m	Bi-oil Rec 1m	bi-term Rec 1m	bi-m1 Rec 3m	bi-term Rec 3m	Trim1m0 Rec 6m	Bi-term Rec 6m	Average
Net Wealth	7287,462	10383	8630,6	10078	11407,12	7962,615	6810,093	6066,909	8762,7
Wealth in relation to b/h	x	3095,9	1343,1	2790,6	4119,655	675,1538	-477,369	-1220,55	1475,2
Mean Return	-0,01709	0,0016	-0,001	0,001	0,020737	-0,00163	-0,00413	-0,00614	0,0015
Std. Deviation	0,143155	0,045	0,0482	0,0412	0,203352	0,062829	0,064315	0,062721	0,0754
Sharpe Yearly	-0,41349	0,1254	-0,09	0,0821	0,353263	-0,09015	-0,22219	-0,33925	-0,026
Sharpe P-value	0,352912	0,6918	0,7766	0,7953	0,265183	0,775631	0,482745	0,284509	0,5817
Jensens Alpha	-0,0136	0,0027	-0,000004	0,0018	0,021777	0,000452	-0,00193	-0,00405	0,003
Jensen P-value	0,881615	0,9764	0,9996	0,9838	0,811474	0,996048	0,98309	0,964588	0,9593

A.7 Graphs

Graph 7.1. Economic results from portfolios

Graph 7.1 illustrates the different performance of a few selected portfolios.



Graph 7.2 OilExch and OMXS30

Graph 7.2 illustrates a comparison between an OMXS30 index and an OilExch price index. We can see that the fit is a lot better for the early time period then for the late one.