Empirical evidence of stock return predictability using macroeconomic variables

Carl Ferm and Jonatan Gustafsson*

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ABSTRACT

We investigate whether macroeconomic variables can predict returns of the OMXS30 index in the short run, and if an investor can generate abnormal profits from using the variables with significant predictive power. Granger causality tests, along with a predictive OLS regression framework show that the first difference of the repo rate and the log difference in exchange rates significantly Granger cause stock returns on the Swedish market. The findings confirm that changes in the repo rate affect stock returns in line with the transmission mechanism effect of monetary policy and supports that currency depreciation negatively affects future stock returns. We also show that an investor could have generated abnormal returns using macroeconomic variables by deploying a regression based rolling window trading strategy, that yielded statistically significant four-factor alpha between 1998-2008 (without considering transaction costs) - although generating lower returns going forward. The strategy's worsened performance is further linked to the negative interest rate regime, creating difficulties to estimate its recent linear interdependency with stock returns that is used to trade on - indicating that the effectiveness of the repo rate as a monetary policy tool affects strategy returns.

KEYWORDS: Granger Causality, Predictive Regressions, Trading Strategies, Macroeconomic Variables, Repo Rate

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*Kindly address correspondence to Jonatan Gustafsson (23596@student.hhs.se) or Carl Ferm (23553@student.hhs.se)

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1 Introduction

The stock market is considered a useful tool for mirroring the state of the economy, and prices should reflect the present value of stock returns. Knowing that macroeconomic variables carry information about the state of the economy, these variables would also in theory hold predictive power with respect to future consumption and investment opportunities, which in turn would affect firms' ability to generate future cash flow. Over the last decades, several studies have tried to investigate the relationship between stock returns and macroeconomic variables. Authors do, however, still not come to conform conclusions regarding which macroeconomic variables that have significant predictive power over stock market returns. The selection of time horizon, country, econometric models and choice of macroeconomic variables are just some of the factors that play a decisive role in what conclusions that have been drawn in previous research, with most papers focusing on U.S. data (e.g. Fama & French (1989), Geske & Roll (1983) and Campbell (1987).

Interestingly, Pesaran and Timmermann (1995) brought the topic of predictability one step further and tested whether predictability could have been exploited by investors in the U.S. using a wide range of financial and economic variables. Later, Marquering & Verbeek (2004) expanded the work and showed that investors could have profited from active asset allocation trading strategies, however with decreasing returns over time, also considering U.S. data. Furthermore, Rapach et al. (2005) studied international stock return predictability using macroeconomic variables and suggested in their conclusions that a potential area for future research would be to test whether an investor could have used one or more significant macroeconomic variables to earn abnormal returns in real time - as opposed to only test for return predictability. This highlights the relevance to elaborate on results of predictability in a way that is specifically aimed at investors in terms of gains from such knowledge. Thus, previous empirical studies and results have paved the way for further assessment of how macroeconomic factors can predict stock returns, and to what extent this information can be exploited by an investor. To extend the previous research, we consider Sweden, which is a small open economy that is less subject to extensive macroeconomic research. Building on the papers of Marquering & Verbeek (2004) and Rapach et al, leads us to the following questions that are to be examined:

I. *Do macroeconomic variables have predictive power with respect to stock returns in Sweden?*
II. *Can an investor earn abnormal returns from using macroeconomic variables to predict stock returns in Sweden?*

To answer the questions, we specifically investigate if certain macroeconomic variables can predict Swedish stock index returns, and if the predictive ability can be exploited to generate abnormal returns by developing trading strategies based on the initial findings. Our data comprises monthly measurements of price levels of the Swedish stock index OMXS30 and macroeconomic factors, including the production value index, the repo rate, inflation, the relative strength of the Swedish krona to other currencies, the slope of the yield curve and money supply. The time period observed is 1998-2018.

Initially, a vector autoregressive (VAR) framework is used to examine the individual relationships between the macroeconomic variables at a given time lag and stock returns, where one lag represents one month. The time lags to be investigated are chosen as suggested by the established Akaike and Schwartz Bayesian information criteria. To be able to interpret the relationships in the VAR model, the Granger causality test is used to test whether any of the variables Granger causes stock returns, i.e. if they have significant predictive power. To complement the analysis, predictive multivariate OLS regressions between future OMXS30 returns and macroeconomic variables will further validate their predictive ability in terms of linear dependences. The outcome of the regressions enables examination and interpretation of the linear relationship between the variables, also considering the direction of the effect of a given variable.

The variables that significantly Granger cause stock returns, and also have a significant linear relationship with future stock returns are selected for the trading strategies, with the aim to investigate if investors can benefit from using these as predictors. To test for the robustness of a given macroeconomic variable as a predictor, two dynamic and two static regression-based strategies are evaluated, where the beta and intercept for the dynamic strategies are re-estimated each month as new information becomes available. All strategies enter a long position in the index if positive returns are predicted in the future period(s) and a short position if negative returns are predicted. The holding period of the strategies correspond to the time lag indicated by the lag selection criteria, which the dependent variable in the regression is also based on. Strategy returns are evaluated based on the extent to which they generate statistically significant and thereby risk adjusted positive Carhart four-factor alpha over the studied period, complemented with mean-variance oriented analysis using the Sharpe ratio.

We find that the first difference in repo rate Granger causes stock returns at a 5% significance level at 7 lags and 1 lag. Also, the change in exchange rate Granger causes the stock returns at a 5% significance level at 7 lags. Heteroscedasticity-robust OLS regressions further confirm statistical causality for the repo rate with respect to both a 1 and 7 month return horizon, for which the variable has a statistically significant negative coefficient. The results are in line with previous findings and suggest that the first difference in repo rate is an appropriate predictor of stock returns, which also is in accordance with the monetary transmission effect, although our results only can confirm statistical significance. The findings on the log-difference in exchange rate are consistent with previous findings in other countries, e.g. Mookerjee & Yu (1997), indicating that depreciation of the currency could be interpreted as increased inflation expectations.

When evaluating the trading strategy results, only the in-sample strategy generated abnormal returns throughout the entire dataset, while no out-of-sample strategy (that would have been practically feasible for an investor to execute in real time) did so. More specifically, the only alpha generated from a realistically feasible trading strategy - using past information to predict and trade on future returns - was generated by a rolling window strategy during the first half of the data sample. The strategy generated 9.16% annualized alpha during that period, although underperforming the other strategies during the second half of the sample. This provides evidence that it has been historically possible to generate risk-adjusted abnormal returns using macroeconomic variables, when not considering transaction costs (which would partly reduce the abnormal return), but that future abnormal return generation using macroeconomic variables is limited.

Furthermore, the general findings include that the rolling window strategy is outperforming the expanding window strategy over time. In addition, it is seen to better predict returns in more volatile periods, which is line with Pesaran & Timmermann (1995), who suggest that the predictability of excess returns is larger at times when volatility is high. However, when the repo rate turns negative, the rolling window strategy sharply underperforms other strategies. This indicates that the fixed linear relationship between lagged repo rate changes and stock returns used in the static strategies better predict stock returns when there is a negative interest rate regime, as opposed to the dynamic rolling window strategy that constantly re-estimates the same relationship over a rolling 12 month period and fails to predict returns when the monetary policy shift to negative rates. Further analysis suggests that the performance of the rolling window trading strategy is affected by the effectiveness of the repo rate as a monetary policy tool, forcing the repo rate to remain at extraordinary low levels due to its recent inability to stimulate inflation.

The conclusions drawn from our findings might contribute with insights to policy makers in terms of highlighting the impact of monetary policy decisions on stock returns, with respect to potential side effects of using the repo rate as a monetary policy tool, given its significant impact on stock returns. Also, we may provide investment managers with insight into methods of predicting stock market returns and executing automated regression based trading strategies – a frequently discussed topic in the modern and increasingly digitized economy. Lastly, the thesis also allows for evaluation of how the negative interest rate environment potentially affects trading strategies.

2 Literature review

2.1 Macroeconomic variables and stock return predictability

Macroeconomic variables' effect on stock returns has previously been studied individually, although primarily in the U.S. This includes variables such as the inflation rate (e.g. Fama 1981 and Geske & Roll 1983), money supply (Hamburger & Kochin 1971), aggregate output (Balvers et al. 1990), interest rates (Campbell 1987) and term spreads on bonds (e.g. Chen 2008 and Bauer 2018). Other papers have also investigated other countries than the U.S., although less extensively. Furthermore, the early papers studying the relationship between stock returns and macroeconomic variables has mainly focused on the contemporaneous relationship, as opposed to a predictive. Since then, many papers have extended the research to more explicitly explore predictive power and forecasting, predominantly so by using predictive regression models and tests based on vector autoregressive models. For example, Rapach et al. (2005) studied macroeconomic variables and stock return predictability across countries using a predictive regression framework with out-of-sample tests based on Granger Causality, finding different results for different economies, likely driven by country specific differences. In the Netherlands, the U.S. and Norway, Rapach et al. found strong evidence of predictive ability using the inflation rate, while not being able to draw conform conclusions for other considered industrial countries. However, a conclusion to bring from the paper is that interest rates were the most consistent and reliable forecasting variables.

Mookerjee & Yu (1997), on the other hand, found that money supply and exchange rates have an impact on future stock returns in Singapore by using the techniques of cointegration and causality together with forecasting equations in the long run as well as the short run. Tripathy (2011) also investigated this certain topic and found that changes in exchange rate and interest rate significantly influence the Indian stock market by using an Autoregressive Integrated Moving Average (ARIMA) time series process and Granger causality tests. Recently, Gupta & Mampho (2013) examined both in and out-of-sample predictability of South African stock returns using macroeconomic variables, and found that interest rates and money supply show short term predictive ability, employing a predictive regression framework for in-sample and MSE-F and the ENC-NEW test statistics for out-of-sample predictability.

Although many papers have been able to find significant relationships between macroeconomic variables and stock returns, there are, however, also papers concluding that the relationship between certain markets and macroeconomic factors is not always definite. For example, Hamburger & Kochin (1971) came to the conclusion that even if changes in monetary growth seem to affect the stock market, a long-term sustainable relationship is unclear. Findings like this open up for further investigation under different macroeconomic conditions and/or in different markets. This was specifically mentioned by e.g. Ferreira & Santa Clara (2011) who predicted stock returns using financial metrics. They concluded that "...the predictability of stock market returns is therefore still an open question".

Although there is lack of focus on smaller open economies, Gjerde & Saettem (1999) focused on the Norwegian market and causal relations between stock returns and macroeconomic variables. They found that real interest rate plays a major role in the Norwegian economy. In that paper, it is also said that "a certain degree of inefficiency seems to be present in the sense that stock returns respond positively and delayed to changes in industrial production". Gjerde & Saettem further suggest that similar studies using a VAR framework should be applied on other small open economies, suggesting Sweden as a suitable candidate given its differences in industry structure compared to Norway.

Lastly, the Swedish market has previously been studied by Ljungstedt (2015), who specifically considers macroeconomic variables impact on the stock market. He finds statistically significant long-term relationships between several macro variables and the stock market using cointegration analysis, including positive long-run relations between inflation, the 10 year Swedish government bond, the SEK/USD exchange rate and the stock market. Therefore, analysis of the Swedish market using a combination of other methods for identifying predictive power remains undone and might provide new insights to the previous research on smaller open economies.

2.2 Investment strategies and stock return predictability

The question of whether macroeconomic variables can predict stock returns naturally leads in to the question whether an investor can gain from such knowledge by earning abnormal returns. This topic was particularly addressed by Rapach et al. (2005) in their conclusions, as a suggestion for future research - questioning whether an investor in real time could have used one or more macro variables to earn extra-normal profits, and to examine whether some variables perform significantly better if one allows for time-varying effects of macro variables on stock returns. This highlights the importance to assess results of forecasting results in a way that is presentable for investors in terms of highlighting how they can increase their utility based on the information.

Pesaran & Timmermann (1995) examined predictability of U.S. stock returns and whether predictability could have been exploited by investors in excess of a buy and hold strategy in the market index, by using recursively estimated regressions over the period 1960-1992. They found that predictive power of various economic variables over stock returns varies over time and that it tends to vary with volatility. Also, they find that it appears to be decreasing strategy returns over time, which is consistent with incomplete learning in the aftermath of a large shock to the economy or alternatively that the predictability of excess returns is reflecting time-varying risk premia.

Marquering & Verbeek (2004) builds on the research of Pesaran & Timmermann, and evaluate different out-of-sample trading strategies on the S&P 500 index using monthly data over the period 1970-2001, with trading rules based on coefficients from lagged regressions on financial and macroeconomic variables (price to earnings ratio, dividend yield, inflation, industrial production, monetary growth, commercial paper-Treasury yield and the 12 month Treasury bill). They also find that predictability of returns is higher when volatility is high, and that asset allocation based active trading strategies outperform static strategies in terms of Jensen's alpha, Sharpe ratios and the Treynor-Mazuy test. They also suggest that the profitability of the strategy was higher in the past, and that decreasing levels of predictability are consistent with "learning in the marketplace" (Pesaran & Timmermann 1995), but may also reflect that there is no stable relationship between asset returns and forecasting variables over time. Furthermore, Narayan et al. (2014) provide evidence of in-sample predictability of stock returns when examining a range of macroeconomic and institutional factors. They used a multivariate predictive regression framework for which coefficients of the model are re-estimated each month when new information becomes available. Their results show that investors could profit substantially from this by using static and dynamic trading strategies based on these factors, estimating returns using a portfolio that purely bases investment decisions on information from their predictive regression model.

Our thesis builds on the work of Marquering & Verbeek (2004) and Rapach et al. (2005) by extending previously used methods to a new economy and explore both stock return predictability and combining it with a pragmatically oriented investor utility based framework in terms of abnormal return generation by applying a framework that is similar to what has previously been used internationally and extending the research to a small open economy, that being Sweden. More specifically, we consider the suggestions of Rapach et al. to consider an investors' possibilities to generate abnormal profits based on analysis of macroeconomic variables' predictive power, by employing an investor based framework (as suggested by Marquering & Verbeek) but using different methods to evaluate the possibilities for an investor to generate abnormal returns. By doing this, we hope to contribute to the existent research both in terms of predictive power with respect to macroeconomic variables as well as in how they specifically can be applied to generate risk adjusted returns using regression based trading strategies in Sweden, which also allows for evaluation of how the negative interest rate environment potentially affects trading strategies.

3 Description of data and variable selection

3.1 Stock return data

Stock return is used as a dependent variable when investigating whether a macroeconomic variable has return predictability, and the data has been collected from Thomson Reuters Eikon. The change in the Swedish OMXS30 index is used as proxy for stock returns, since it has easily accessible historical data and includes many of the largest publicly traded companies, which likely are exposed to effects of macroeconomic factors. More precisely, the OMXS30 index comprises a value weighted portfolio of the 30 most traded companies on the Swedish stock exchange. By choosing an index which only includes the most traded companies, being frequently followed by equity analysts and very liquid, we optimize the selection with regards to investigating stocks that are correctly priced based on all available information.

3.2 Macroeconomic data and variable selection

All macroeconomic data has been collected from Sveriges Riksbank, Statistics Sweden and Thomson Reuters Eikon. The selection of variables is mainly based on what has been found in previous international research of macroeconomic variables' predictive power with respect to stock returns, and variables are selected on an individual basis. Thereby, we aim to evaluate traditional macroeconomic variables that preferably are uncorrelated, with the aim to take into account a broad spectra of potential effects considering only a few variables. The variables selected are the *repo rate*, *inflation, exchange rate, money supply, yield curve slope* and *aggregate output*. In the following body of text, arguments for the variable selection are presented - supporting our choices and each variable's importance in explaining stock returns.

Campbell (1987) mentions that short-term interest rates have tended to be negatively correlated with stock returns in the U.S. The relationship between interest rates and stock price development is further confirmed in several papers, including Alam & Uddin (2009). Therefore, we use the Swedish repo rate since it is strongly correlated with market interest rates and is set directly by the central bank. The repo rate further affects asset prices via the transmission mechanism of monetary policy (European Central Bank 2018), which has a positive relationship with market rates and thereby directly affects discount rates for financial assets. Also, it indirectly affects stock returns via increasing borrowing costs of financial institutions, effects of future consumption and firm investment decisions in the economy (Finansdepartementet 2014).

The first difference of the repo rate is chosen to represent this macroeconomic factor, as opposed to using the variable without considering change. The reason for that is both to have consistency in the model and to get more comparable results, since all other variables in the model are based on change data. Also, formatting by logarithmic difference is not appropriate given its small values measured in this dataset, overstating the percentage change, and given that the variable is already stationary since it is not a cumulative index such as e.g. OMXS30. The data considering the repo rate comprises historical values on a monthly basis which are collected from the Swedish Riksbank's webpage.

We will also use the change in the slope of the yield curve (i.e. the difference between a long and short maturity government bond) as a factor used for prediction of stock returns, since it has been proven to have explanatory power of the stock market in, for example, the U.S. (Chen 2008). Wide spreads between short-term and long-term bonds lead to an upward sloping yield curve, which can indicate healthy economic prospects - most likely faster growth and inflation in the future. On the other hand, narrower spreads lead to a flatter or even negatively sloped yield curve, which can indicate poor economic prospects which likely implies decreased growth and inflation. The term spread predictability over stock returns was further confirmed by Bauer (2018), who defined the variable as the difference between U.S. 10 year and 1 year government bonds. However, given that Sweden does not issue 1 year government bonds, but only 2 year maturity bonds and longer, we will define the spread as the difference between the 10 year and the 2 year government bond.

Another macroeconomic variable that has been proved to have predictive power regarding stock returns is aggregate output. For example, Balvers (1990) proves this relationship to be positive and significant. A widely used definition of aggregate output for a country is Gross Domestic Product (GDP). However, the GDP of Sweden is only available on a quarterly basis, and since monthly data will be used throughout the study, a proxy has to be used instead. A proven output factor that has been investigated in several papers is industrial production, which is used in Balvers (1990). Due to the relatively poor availability of monthly output data regarding industrial production, and given the cyclical characteristics of the construction industry, growth in the Production Value Index (PVI) for the construction industry will instead be used as a proxy for GDP growth. It is assumed to have a positive relationship with stock returns since it can be seen as an indicator of how the economy is performing. Furthermore, this variable may inherently have more predictive power for the stock market compared to GDP given the construction industry's cyclical characteristics.

Inflation is another factor that has been frequently investigated regarding its capabilities to predictive stock returns, and previous research has concluded that it has significant predictive power. Based on the results from e.g. Fama (1981) and Gupta & Mampho (2013), inflation is found to have a strong negative correlation with future stock returns in the U.S. and South Africa respectively. Based on these findings, amongst others, high inflation is assumed to indirectly increase the discount rate of stocks, thereby showing an inverse relationship. When inflation increases, purchasing power declines, and each unit of currency can buy fewer goods and services. For investors interested in income-generating stocks, or stocks that pay dividends, the impact of high inflation makes these stocks less attractive than during low inflation, since dividends tend to not keep up with inflation levels.

Gupta & Mampho (2013) and Mookerje & Yu (1997) investigated which macroeconomic variables that affect South Africa's and Singapore's stock markets respectively. Both papers found that money supply has predictive power. The effect of money supply has been shown to positively impact growth rates of dividends, and negatively impact the discount rate and risk premium, e.g. documented by Homa and Jaffee (1971). Thereby, we will include money supply as an independent variable in this study as well. We have defined money supply as M3 in Sweden, since that is the broadest measure, including additional components mainly relatable to financial institutions and larger corporations.

Since Sweden and its stock market is heavily dependent on exports, the exchange rate is of high importance for company and stock performance. This idea is supported by findings from e.g. Tripathy (2011) who founds that the exchange rate significantly influences stock market performance by affecting companies' overseas performance. Therefore, the Swedish central bank's Total Competitiveness Weight-index (TCW) is selected to study the change in the value of the Swedish Krona over time. More specifically, the TCW-index weights different bilateral exchange rates to create an effective (or average) exchange rate. It is a geometric index and its weights are based on the average aggregate flows of processed goods for 21 countries. A higher value in the index means that the krona has depreciated and a lower value means that the krona has appreciated.

3.3 Variable formatting

Given that time series data is analysed, several potential problems emerge, including heteroscedasticity, autocorrelation and stationarity. Therefore, the independent macro variables are formatted by considering the monthly percentage change, except for the variables already presented in percentage when collected. The latter are only transformed by considering the first difference, i.e. subtracting the previous period's value from the current period's value. The data is further transformed to have a more linear development by logarithmic transformation of some of the variables' change. This logarithmic transformation is useful for smoothening of the changes and tailor the variables to better suit linear regressions of the data - increasing their linear characteristics and thereby the explanatory power. Finally, all variables are expressed in percentage-form, as opposed to decimal-form, hence the multiplication by 100.

For the dependent variable, the monthly change in closing prices of the OMXS30 stock index obtained from Thomson Reuters Eikon, *Return*, is observed and transformed by dividing the index value in period t by the index value in period $t-1$. The change is logarithmically transformed to create a more linear data set, and multiplied by 100 to obtain the percentage change. Going forward, new return variables using different time lags, *ReturnFW(j)*, will be defined where *j* is the lags selected. This formatting is further elaborated on in the methodology. However, the calculation of the *Return* variable can be described as presented in the following equation:

$$Return_t = ln\left(\frac{OMXS30_t}{OMXS30_{t-1}}\right) \cdot 100$$

The repo rate is collected from the Riksbank, and the *dRepo* variable is the nominal change between monthly time periods. Thus, *dRepo* is calculated as follows:

$$dRepo_t = (Repo_t - Repo_{t-1}) \cdot 100$$

The exchange rate variable used, *dTCW*, is obtained from the TCW index available at the Riksbank website. The logarithmic percentage change of the TCW index between two following months is calculated as described in the equation below:

$$dTCW_t = ln\left(\frac{TCW_t}{TCW_{t-1}}\right) \cdot 100$$

The logarithmically transformed difference in consumer price index, *Inflation*, comprises all items for Sweden. The underlying data is collected from Thomson Reuters Eikon, and *Inflation* is calculated as follows:

$$Inflation_t = ln\left(\frac{CPI_t}{CPI_{t-1}}\right) \cdot 100$$

The change in the slope of the yield curve, *dSlope*, is calculated as the nominal difference between the Swedish 10 year and 2 year government bonds (GVB) in period t and period $t-1$. The difference is presented in percentage, thereby being multiplied by 100. Data is collected from the Riksbank. The variable is calculated as follows:

$$dSlope_t = \left((GVB_t^{10Y} - GVB_t^{2Y}) - (GVB_{t-1}^{10Y} - GVB_{t-1}^{2Y})\right) \cdot 100$$

Money supply is defined as the M3 amount as mentioned above. This dataset is collected from the Thomson Reuters Eikon database. The growth in money supply is logarithmically transformed, creating *gMS*, and calculated in the following way:

$$gMS_t = ln\left(\frac{MS_t^{M3}}{MS_{t-1}^{M3}}\right) \cdot 100$$

The production value index (PVI) growth, *gPVI*, is collected from Statistics Sweden and is calculated in accordance with the equation below:

$$gPVI_t = ln\left(\frac{PVI_t}{PVI_{t-1}}\right) \cdot 100$$

3.4 Descriptive statistics of the data

TABLE 3.1

DESCRIPTIVE STATISTICS OF THE SELECTED VARIABLES

Descriptive statistics of the dependent variable *Return* and the independent macroeconomic variables that are to be investigated

	Obs.	Mean	Std.Dev	Min	Max
Return	239	0.327	5.713	-18.466	16.178
dRepo	239	-0.020	0.153	-1.105	0.357
Inflation	239	0.098	0.407	-1.352	1.021
gPVI	238	0.228	12.371	-46.954	41.837
dTCW	239	0.042	1.345	-5.797	4.544
gMS	239	0.576	1.334	-3.446	5.183
dSlope	239	0.003	0.143	-0.634	0.531

Note: All values are presented in percentage.

4 Methodology

4.1 The vector autoregressive model

Using a vector autoregressive (VAR) model enables the capturing of linear dependencies between multiple time series and at different lags. This is obtained by describing the evolution of a variable as a linear function of its own lagged values, other variables' lagged values and an error term. The model allows for multivariate time series, which is the case in the investigation regarding the relationship between different macroeconomic factors at different lags and stock returns. Furthermore, it is particularly useful for describing the dynamic behaviour of economic and financial time series as well as for forecasting, according to e.g. Zivot & Wang (2006).

The VAR model thereby provides us with the linear relationship between one of the *n* variables, independent as well as dependent, and its own lagged values as well as the other variables' lagged values at all lags up until the maximum lag j. All variables are arranged into a single (*n* x 1) vector y_t, from which the lagged macroeconomic variables' ability to forecast stock market returns can be investigated.

In its unrestricted form, the VAR(*j*) model is specified as follows:

$$y_t = \alpha_0 + \sum_{i=1}^{j} A_i y_{t-i} + \varepsilon_t$$

The model comprises the following variables, where

α_0 is the intercept term

A_i is an (*n* x *n*) matrix of unknown coefficients

j is the number of lags

ε_t is an error term with zero mean and no serial correlation

The vector autoregression is, as earlier mentioned, conducted to investigate the linear interdependencies between, and dynamics of, lagged values of the macroeconomic variables and OMXS30 returns over time. Since the VAR compares the variables individually, it is not necessary to specify dependent and independent variables. However, this model cannot be used to adequately interpret the relationship between multiple variables. Therefore, a Granger causality test will be the main test for investigating macroeconomic variables' predictive power for stock returns. It is commonly used within the research area of predictability as it structurally summarizes and analyzes the VAR model. Since the VAR model provides a natural framework of all variables' linear interdependencies, it enables the Granger causality test to investigate whether any of the macroeconomic variables have predictive ability over stock returns at a certain lag. Thereby, performing the VAR is necessary for conducting Granger causality tests, although not being the optimal test to interpret results from.

4.2 The Granger causality test

The Granger causality test is a statistical test that is useful for testing whether one time series is useful in forecasting another. This characteristic makes the test suitable for empirical investigations regarding statistical cause-effect relationships, i.e. whether a time series' values precede another time series' values, thus making it suitable for this study. As mentioned previously, the test structurally summarizes properties of the VAR model. If values of X provides statistically significant information about future values of Y, X is said to Granger cause Y. The following fundamental principles of causality as described by Granger (1969, 1980) as:

I. The effect does not precede its cause in time
II. The causal series contains unique information about the series being caused that is not available otherwise

Given these assumptions about causality, the following proposition is made to test the following hypothesis for identification of a causal effect of X on Y:

$$Prob(Y_{t+1} \in A \mid \Omega_t) \neq Prob(Y_{t+1} \in A \mid \Omega_t - X_t)$$

Where

A	is an arbitrary non-empty set
Y & X	are two random variables in the universe
Ω_t	denotes all information available in the entire universe at time t
$\Omega_t - X_t$	denotes all information available in the entire universe at time t when X is excluded

If the above hypothesis is accepted, X is said to Granger cause Y. The test investigates whether any of the macroeconomic factors used in the VAR model, as well as throughout this paper, significantly add value to predict future stock returns compared to only using lagged stock returns for prediction as the variable evolves. That is, if past values of X(back until time $t - j$) at time t contains unique information that increases the predictability of Y_{t+1}, X is said to granger cause Y. If the null hypothesis that no explanatory power is added by considering the additional time series is rejected, implying that the alternative hypothesis is accepted and that the time series thereby add predictive power, i.e. variable X Granger causes Y.

4.3 Lag selection

The VAR model and Granger causality tests are sensitive to the number of lags (e.g. Thornton and Batten 1985), therefore, the lag selection is of high importance to avoid misleading statistical evidence when testing for Granger causality. In previous papers, both the Akaike Information Criterion (AIC) and the Schwarz's Bayesian Information Criterion (SBIC) are frequently used. The criteria are defined as the equations shown below, where *LL* is the log likelihood for a VAR(j), *T* is the number of observations, t_j is the number of estimated parameters when considering *j* lags.

$$AIC = -2\left(\frac{LL}{T}\right) + \frac{2t_j}{T}$$

$$SBIC = -2\left(\frac{LL}{T}\right) + \frac{ln(T)}{T} t_j$$

When using these criteria, the lag with the lowest AIC or SBIC value is the best fitting selection of lags according to each model. The AIC is often less penalising (i.e. increasing the score with a lower amount) when it comes to including additional lags to fit an optimal explanatory model for the data, often suggesting a higher number of lags as the optimal selection for creating a "true" model. This is particularly important when having a fair amount of observations because of the replacement of 2 in the penalizing factor of AIC with *ln(T)* in the SBIC, giving the criterion a higher value when increasing the number of lags for the SBIC relative to the AIC.

The AIC criterion has been shown by Shibata (1976) to balance well between the problems of generating biased estimates due to too few lags included and increased complexity due to too many lags, thereby having too many regressors included. Shibata (1976) also mentions that when the correct number of lags is unclear, thus being hard to decide, the consistency of a model selection criterion is not as important - opening up for the usage of the AIC. On the other hand, it is sometimes preferred to use the most parsimonious model, i.e. the model with the lowest number of lags, given that all models specified are correct. When it comes to taking this issue into consideration, the SBIC is often preferred as it penalizes additional lags to a higher extent compared to AIC. Thus, it however requires that the relationship fits relatively well to a simple model using a small amount of parameters.

According to Kuha (2004), both criteria are useful for finding a correct model. He further mentions that AIC is a popular criteria within econometrics. To be able to come up with a conclusion and results based on a solid foundation, suggestions from both the popular, yet sometimes overfitting, AIC and the more prudent SBIC will be used to find the optimal number of lags according to each criteria.

4.4 OLS regression framework

The Granger causality test is primarily used to find which variables that cause stock returns. However, to estimate the direction and magnitude of macroeconomic variables' ability to predict stock returns, multivariate predictive OLS regressions are conducted for stock returns r between time t and $t + j$ and the macroeconomic variables at time t, to further assess the predictive ability over the time horizons suggested by the AIC and SBIC. New variables thereby have to be defined, given the indication of the lag selection criteria, to be able to explore the predictability of stock returns over the different horizons. The new return variable(s) will be defined as follows:

$$ReturnFW(j) = r_{t,t+j} = ln\left(\frac{OMXS30_{t+j}}{OMXS30_t}\right) \cdot 100$$

The predictive multivariate regressions are undertaken in the following way:

$$r_{t,t+j} = \beta_0 + \beta_{dRepo} \cdot dRepo_t + \beta_{Inflation} \cdot Inflation_t + \beta_{gPVI} \cdot gPVI_t + \beta_{gPVI} \cdot gPVI_t + \beta_{dTCW} \cdot dTCW_t + \beta_{gMS} \cdot gMS_t + \beta_{dSlope} \cdot dSlope_t + \varepsilon_t$$

The beta coefficients generated in the predictive regressions are used to investigate which variables that significantly contributes to the estimated linear relationship between future stock returns and the macroeconomic variables. These coefficients will further indicate whether each variable has a negative or positive effect on future stock returns, and to what extent a change in a certain variable affects returns.

4.5 The trading strategy

To evaluate to what extent an investor can earn abnormal risk adjusted returns based on predictions of stock returns, we use trading strategies based on macroeconomic variables. The variables used in the trading strategy will be the ones that both Granger cause stock returns and show evidence of a statistically significant coefficient in the OLS regression. The actual trading strategy is based on a bivariate regression framework between stock returns and lagged values of the macroeconomic variables on a stand-alone basis - generating a b_0 and b_1 that explain their interdependencies. This method enables the prediction of stock returns by creating a linear function which uses the intercept and beta from the regression, and the selected macroeconomic factor as independent variable. Depending on if the predictive function predicts a positive or negative return, a long or short position respectively is entered in period *t* and held until period *t+j*. More specifically, the separate trading strategies are set up based on the following rules:

Long position in period *t* until *t+j* if: $r_{t,t+j} = b_0 + b_1 \cdot x_t > 0$

Short position in period *t* until *t+j* if: $r_{t,t+j} = b_0 + b_1 \cdot x_t < 0$

Where:

$r_{t,t+j}$	is the stock returns between period *t* and *t+j*
b_0	is the intercept in a lagged regression with j lags
b_1	is the beta value in a lagged regression with j lags
x_t	is a statistically significant macro variable in time period *t*.

The return is realized in period *t+j,* that is a period in the future with respect to *j* lags. Excess returns from the different trading strategies are then regressed against the Carhart four factors to identify potential pricing errors and assess if an investor could have generated abnormal profits using trading rules based on the statistical tests. To test the robustness of the macroeconomic variable as a predictor, two different types of trading strategies are tested: static and dynamic.

4.5.1 Static regression trading strategies

The static trading strategies are conducted in two ways; in-sample and out-of-sample. In general, in-sample tests imply that the regression which generates the b_0 and b_1 factors is based on the same data sample as the trading strategy is applied on, i.e. the total time series. Thereby we consider a historical relationship and explore whether this relationship could have been used to trade on during the same period. Out-of-sample trading strategies instead perform a regression on historical data to use the generated b_0 and b_1 for predicting returns and trading on the predictions in future periods.

For the static out-of-sample strategy, we estimate the intercept and coefficients by regressing the chosen lagged macroeconomic variable against stock returns in the first half of the time series to predict stock returns during the second half. This method assumes that the relationship estimated in the first half between the macroeconomic variable and future stock returns will remain in the second half and that returns can be predicted using it. Considering the in-sample static trading strategy, the total time series is used to regress the chosen variable against future stock returns, and the generated coefficient and intercept are used to predict stock returns throughout the same period.

4.5.2 Dynamic regression trading strategies

To capture how investors can profit from more dynamic trading rules based on regressions on single macroeconomic variables, out-of-sample regressions with changing time windows are developed so that intercepts and coefficients are continuously re-estimated every time period. Two approaches of rolling bivariate regressions are applied for the dynamic trading strategies, being:

i) Rolling window regressions, with a window of 12 months, where intercepts and coefficients used for prediction are recalculated every period, based on the previous 12 months in the time series, including the current time period, impacting the trading decision in every period. Using a rolling 12-month time window thereby allows for time varying dynamics in the relationship between stock returns and lagged changes in either of the selected macroeconomic variables.

Under a basic bivariate regression framework

$$r_{t,t+j} = b_0 + b_1 \cdot x_t + \varepsilon_t$$

The estimate for $y_t = r_{t,t+j}$ will be given as

$$\hat{y}_t = b_{0,t}^R + b_{1,t}^R \cdot x_t + \varepsilon_t$$

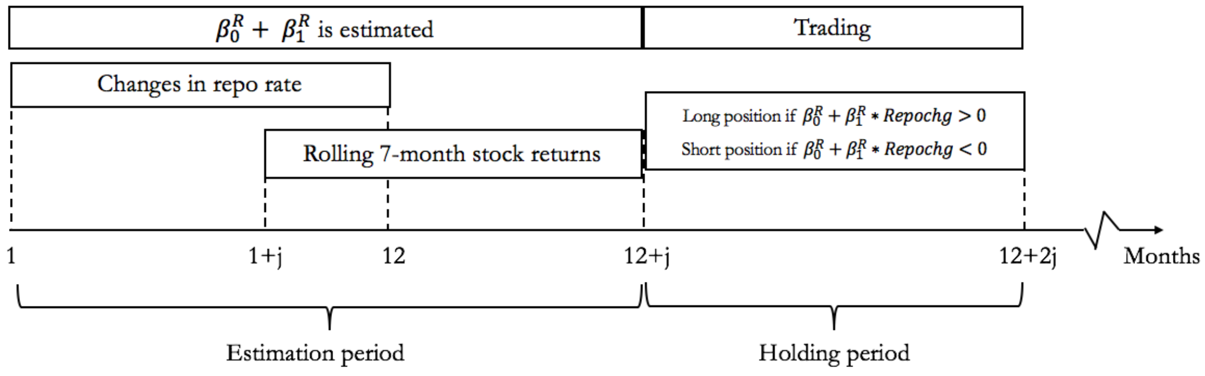
$$b_{1,t}^R = \frac{\sum_{i=t-11}^{t}\left(x_{i-j} - \bar{x}\right)\left(y_i - \bar{y}\right)}{\sum_{i=t-11}^{t}\left(x_{i-j} - \bar{x}\right)^2}$$

$$b_{0,t}^R = \bar{y} - b_{1,t}^R \cdot \bar{x}$$

Figure 4.1 shows how the rolling window strategy is executed for returns with a time lag of *j* months, for which *j* corresponds to 7 months in the example given.

FIGURE 4.1

EXECUTION OF THE ROLLING WINDOW STRATEGY



ii) Expanding window regressions is the second dynamic strategy, developed to capture a more realistic version of in-sample trading strategies that an investor could technically not implement in reality. This method dynamically captures the accumulation of data from previous periods and approximates a feasible version of the in-sample method.

The estimate for $y_t = r_{t,t+j}$ will be given as

$$\hat{y}_t = b_{0,t}^E + b_{1,t}^E \cdot x_t + \varepsilon_t$$

$$b_{1,t}^E = \frac{\sum_{i=t_0+j}^{t}(x_{i-j} - \bar{x})(y_i - \bar{y})}{\sum_{i=t_0+j}^{t}(x_{i-j} - \bar{x})^2}$$

$$b_{0,t}^E = \bar{y} - b_{1,t}^E \cdot \bar{x}$$

Both dynamic trading models still follow the initial trading rules as the static models use, and assumes that coefficients and intercepts are known at a certain date (since changes in a certain variable becomes public on that date) and that an investor can trade that same day, as he will know the relevant parameters for updating the regression and will therefore trade simultaneously.

4.6 Evaluation of trading strategy results

To evaluate the returns of the trading strategies, the Carhart four-factor model is used (Carhart 1997), which is an extension of the Fama-French three-factor model. The factors are constructed by the Swedish House of Finance, calculated over every Swedish stock and aggregated by month. The trading strategies' returns in excess of the 1-month Swedish treasury bill, EXR_t, are regressed against the factors in the following Carhart four factor-model:

$$EXR_t = \alpha^c + \beta_{RMRF} \cdot RMRF_t + \beta_{SMB} \cdot SMB_t + \beta_{HML} \cdot HML_t + \beta_{MOM} \cdot MOM_t + \varepsilon_t$$

Where

EXR_t	is the excess returns of the strategy being tested
α^c	is the pricing error, alpha
$RMRF$	is the excess returns of the market, i.e. $R_m - R_f$
SMB	is a self-financing portfolio that takes a long position in stocks with low market capitalization and takes a short position in stocks with high market capitalization
HML	is a self-financing portfolio that takes a long position in high book-to-market stocks and a short position in low book-to market stocks
MOM	a self-financing portfolio that takes a long position in previous 12-month return *winner* and short previous 12-month *loser* stocks.

The regression results reveal the trading strategies' monthly premium of the different factors and to what extent a given strategy generates statistically significant four-factor alpha, i.e. whether the investment strategy has a return in excess of the reward for the assumed risk. For strategies predicting returns more than one month ahead, the corresponding Carhart four factor returns in the model are recalculated to correspond to the same period so that monthly discrete returns for factor X used in a regression based trading strategy lagged by j months is defined as:

$$X_{t+j} = \left(1 + \frac{X_t}{100}\right) \cdot \left(1 + \frac{X_{t+1}}{100}\right) \cdot \ldots \cdot \left(1 + \frac{X_{t+j}}{100}\right) \cdot 100$$

The Sharpe ratio is also commonly used to measure risk adjusted returns when taking diversification and portfolio construction into consideration.

$$SR = \frac{E[r_p] - r_f}{\sigma_p}$$

The diversification aspect is, however, not an issue when evaluating the strategies against each other as well as against the market, due to that the "portfolios" comprise similar underlying assets, although RMRF enjoys marginally increased diversification benefits from holding more than 30 stocks in the underlying portfolio. The ratio enables us to consider excess return in comparison to total risk, measured as volatility, of the different returns although not focusing on the construction of the portfolios used. Hence, this measure will also be used for evaluating the different strategies under a mean-variance framework.

5 Evaluation of model assumptions

Several assumptions are underlying the statistical models used, which are needed to be fulfilled to generate reliable results and enable us to draw correct conclusions from the tests. For example, the VAR model requires variable stationarity, further discussed below. For the purpose of valid statistical analysis based on OLS regressions, evaluation of OLS assumptions is also conducted below. When estimating the predictive regression models for trading, OLS assumptions are, however, assumed to hold. However, these assumptions are not evaluated explicitly, because of the fact that intercepts and coefficients only are used for trading decisions, and that the trading results are evaluated separately in the Carhart four factor framework.

5.1 Test for stationarity and unit roots

To be able to use the VAR model, the time series data has to be stationary. For a stochastic process to be considered stationary, the time series must have constant mean, variance and autocorrelation structure that are constant over time. Before variables are formatted by calculating the first log-differences, non-stationarity is likely to persist because of behaviours such as random walks, trends and cycles or the combination of them in a time series, for which relationships between variables are likely to be spurious. However, by using the log-difference for a majority of the variables, further motivated in the methodology part, the presence of non-stationary variables is inhibited. This is illustrated for the OMXS30 variable before and after being formatted to *Return* in Figure A. Furthermore, the Augmented Dickey-Fuller test tests the null hypothesis that the variable contains a unit root, with the alternative hypothesis that it is stationary. We can clearly reject the null hypothesis in accordance with Table A. The rejection implies that the time series is stationary, thus being useful for time series analysis.

5.2 Heteroscedasticity

A heteroscedasticity test using the Breusch–Pagan test for linear regression models is conducted for the different regressions. For the regression of the dependent variable for 1 lag, it can be seen in Table B that the null hypothesis of constant variance cannot be rejected, thus confirming that the data is homoscedastic and that all coefficients are correctly estimated. However, for 7 lags heteroscedasticity is not rejected, meaning that coefficients in a multiple regression for 7 lags would not be correctly measured. Therefore, heteroscedasticity-robust standard errors are instead used to allow for the fitting of a model that does not contain heteroscedastic residuals and hence obtain correctly estimated coefficients, using the Newey-West regression.

5.3 Multicollinearity

By observing correlations between the independent variables, the possible problem of multicollinearity in the test statistics is investigated. If independent variables are highly correlated, it is hard to entangle which effect on the dependent variable that is attributable to a certain independent variable - thus making it hard to get reliable results from the regression. However, it does not appear to be a problem with multicollinearity, given that no variables are highly correlated with each other as can be seen in table C1 and C2 which show a correlation table and variance inflation factor test respectively.

5.4 Autocorrelation of residuals

To test for autocorrelation in the residuals, Durbin-Watson tests are conducted, with the output shown in table D. The tests are based on the residuals of the regressions on future values of the Return variable and the macroeconomic variables. For the regressions using 1 and 7 lags, the d-statistic is 1.844 and 0.338 respectively. This shows that there may be positive autocorrelation - implying that after an increase in stock return, another increase will follow in the next period. To still have valid test statistics and standard errors, we correct the predictive regression by running a regression with Newey-West standard errors, which is in accordance with what Newey and West (1987) suggested.

5.5 Omitted variable bias

The purpose of this paper is not to perfectly explain future stock market development in terms of modelling and obtaining a maximum R-squared in a regression, but rather to determine the predictability of traditional macro variables individually. Therefore, the robustness of the models used is potentially subject to omitted variable bias in the regressions, however, the problem does not have any condemning impact on the relevance of the results.

5.6 Normally distributed residuals

Although the residuals from the regressions on future stock returns appear to be normally distributed when observing Figure B1 and B2, we learn from the Jarque-Bera test that we must reject the null hypothesis of normally distributed residuals. This can be seen in the output in Table E. However, the t-tests and linear regressions are not deemed invalid simply because of non-normally distributed residuals. While the t-tests and linear regressions are valid even in very small samples if the outcome variable is normally distributed, their major usefulness comes from the fact that in large samples they are valid for any distribution. This validity is demonstrated by Lumley et al. (2002) who simulate extremely non-normal data. Given the relatively large sample size of more than 200 observations, we therefore assume that the OLS assumptions hold.

6 Empirical findings

6.1 Evidence of macroeconomic variable's effect on stock returns

Since the AIC suggests a selection of 7 lags for the full dataset and the SBIC suggests 1 lag according to Table D, Granger causality tests are conducted for both 7 and 1 lags of the macroeconomic variables.

TABLE 6.1

GRANGER CAUSALITY WALD TEST							
		H_0: the variable does not Granger cause OMXS30 returns at 1 month lag			H_0: the variable does not Granger cause OMXS30 returns at 7 months lag		
Equation	Excluded	chi2	df	Prob > chi2	chi2	df	Prob > chi2
Return	dRepo	4.1883	1	0.041*	18.015	7	0.012*
Return	Inflation	2.6046	1	0.107	13.818	7	0.055
Return	gPVI	2.577	1	0.108	7.4085	7	0.388
Return	dTCW	0.40064	1	0.527	15.891	7	0.026*
Return	gMS	0.17712	1	0.674	7.7632	7	0.354
Return	dSlope	2.4567	1	0.117	7.3994	7	0.389
Return	ALL	10.43	6	0.108	91.68	42	0.000***

*p-value < 5% **p-value < 1% ***p-value < 0.1%
Note: The Granger causality tests indicate which macroeconomic variables that have predictive ability regarding stock market returns. The significant variables are shaded

As indicated by the Granger causality tests in Table 6.1, the change in repo rate Granger causes stock returns at a 5% significance level at 7 lags and 1 lag. Also, the change in exchange rate Granger causes stock returns at a 5% significance level at 7 lags. The predictive regressions (shown in tables G1 and G2) confirms the statistical significance of the repo rate change but does not indicate the same result for change in exchange rates - supporting the usefulness of the first difference in repo rate as a macro variable predicting future changes in equity prices. The strong statistical causality of the change in repo rate further confirms the findings of Rapach et al. (2005), who highlight that relative change in both short term interest rates and money market rates stand out as reliable in-sample predictors compared to other macro variables in explaining stock returns. They also specifically confirm the statically significant negative coefficient for the relative money market rate in Sweden. The direction of the effect is in line with theories regarding the transmission mechanism effect of monetary policy on equity prices (which mainly occurs through the interest rate channel), given that the predictive regressions over both horizons generate negative coefficients. Evidence suggests that stock returns are effected through the link to market rates, as well as the indirect effect of increased borrowing costs of financial institutions, effects of future consumption and firm investment decisions in the economy. Furthermore, the negative coefficient also supports the idea that higher interest rates in terms of monetary policy restrict investor risk appetite, e.g. documented by Lian et al. (2018).

Regarding the statistical causality of the effect of change in the exchange rate on stock returns, the coefficient for the variable is not statistically significant in the predictive regression, which limits strong conclusions of the linear relationship. Thereby, there is not enough evidence to reject the null hypothesis that the coefficient is equal to zero at a given significance level, although one cannot claim with certainty that there is no effect, because of the possibility of a type II error to incorrectly accept a false null hypothesis.

However, since the exchange rate changes Granger causes stock returns over the longer horizon, we still consider the variable to establish the direction of the effect. The negative coefficient for the variable implies that domestic currency depreciation has a negative relationship with stock returns in the following period. This finding is consistent with Hwang (2003), who finds that domestic currency depreciation in Korea has a negative short run effect on stock prices, which also is in line with the findings of Mookerjee & Yu (1997). The latter find that the unanticipated component of exchange rate changes has a positive effect on stock returns in Singapore, suggesting that higher exchange rates lead to higher profit projections, presumably because of lower import costs - which most likely would be a similar effect applicable for Sweden, given the similarities with Singapore in terms of being a small open economy. Another potential reason for the sign of the coefficient could be that a depreciation of the currency could be interpreted as increased inflation expectations in the market stemming from e.g. imported inflation (Federal Reserve Bank of St Louis 1989), increased domestic demand and less incentives to cut costs for domestic manufacturers, thereby negatively influencing the stock market.

The Granger causality tests and predictive regressions widely confirm previous international research on macro variables' effect on equity prices considering short term interest rate changes and changes in the exchange rate. Meanwhile, the other variables assessed do not show any statistical significance in terms of Granger causality. However, the 7 month stock return regression, presented in table G2, shows that inflation and change in the production value index are statistically significant on the 5% level, meaning that monthly changes in these variables have a linear relationship with 7 month stock returns on a monthly rolling basis - although this does not reflect predictability to the same extent as Granger causality. In essence, this widely confirms the general findings of Rapach et al. (2005), as well certain findings on a country specific level, including Tripathy (2011).

6.2 Trading strategy results

6.2.1 Trading strategy variable selection

The lag selection information criteria AIC and SBIC suggested that the macroeconomic variables best predict stock returns under lags of 7 and 1 months respectively. Following that, the Granger causality tests at these lags indicated that the first difference in repo rate for both horizons and change in Exchange rate for 7 lags significantly Granger cause stock returns - making them good predictors of future returns. To further determine the direction and magnitude of the statistical causality, multivariate predictive OLS regressions based on future OMXS30 returns at a 1 and 7 month horizon accompany the Granger causality analysis. In accordance with tables G1 and G2, the regressions showed evidence of a significant beta coefficient between the repo rate and the stock returns at both 1 and 7 months, but no statistical significance was established for changes in exchange rate. Since no significant linear relationship is found for the exchange rate variable, limiting the accuracy of predicting future returns using a linear model, only the repo rate variable is to be used for the trading strategies at 1 lag and 7 lags respectively.

6.2.2 Characteristics of the different strategies

TABLE 6.2

REGRESSIONS ON THE 7 MONTH TRADING STRATEGIES USING THE CARHART FOUR FACTORS

	Regression on the trading strategies' excess returns when predicting stock market excess returns for the next 7 months			
	OutStatRepo7m	InStatRepo7m	ExpRepo7m	RollRepo7m
RMRF7m	0.348*** (3.95)	0.420*** (7.13)	0.312*** (4.73)	-0.00403 (-0.07)
HML7m	0.206 (1.21)	-0.203*** (-3.42)	-0.328*** (-4.96)	-0.293*** (-4.74)
SMB7m	-0.255 (-1.94)	-0.104 (-1.34)	-0.144 (-1.68)	0.0446 (0.55)
MOM7m	-0.0552 (-0.47)	-0.122** (-3.13)	-0.116** (-2.71)	0.327*** (8.46)
_cons	2.035 (1.42)	4.140*** (3.36)	0.246 (0.18)	2.109 (1.67)

*p-value < 5% **p-value < 1% ***p-value < 0.1%

Note: The values in the parentheses are the test statistics, and the other values are the beta exposure to each portfolio. All portfolios are value weighted. Due to that the Carhart four factors only are available on a monthly basis until January 2017, the regression is only conducted using data until that date

TABLE 6.3

REGRESSIONS ON THE 1 MONTH TRADING STRATEGIES USING THE CARHART FOUR FACTORS

	Results from the regression on the trading strategies' excess returns when predicting stock market excess returns for the next month			
	OutStatRepo1m	InStatRepo1m	ExpRepo1m	RollRepo1m
RM_RF_monthly	0.274** (2.92)	0.429*** (6.45)	0.341*** (4.63)	0.0241 (0.33)
HML_vw	-0.184 (-1.15)	-0.117 (-1.70)	-0.0669 (-0.88)	-0.107 (-1.44)
SMB_vw	-0.408*** (-3.61)	-0.249*** (-3.44)	-0.0785 (-0.98)	0.0672 (0.87)
MOM_vw	-0.114 (-1.03)	0.0233 (0.49)	0.221*** (4.14)	0.331*** (6.45)
_cons	0.819 (1.94)	0.490 (1.44)	-0.209 (-0.55)	0.590 (1.60)

*p-value < 5% **p-value < 1% ***p-value < 0.1%

Note: The values in the parentheses are the test statistics, and the other values are the beta exposure to each portfolio. All portfolios are value weighted. Due to that the Carhart four factors only are available on a monthly basis until January 2017, the regression is only conducted using data until that date

By regressing the Carhart four factors on strategy returns, it can be observed that only the in-sample strategy for the 7 month horizon generated statistically significant alpha over the full sample, whilst the rolling window strategy generated significant alpha in the first half of the dataset (seen in table I2). The outcome of the regressions of strategy returns against the Carhart four factors are displayed in tables 6.2 and 6.3, along with descriptive statistics in table H1.

Considering the in-sample static trading strategies, they are expected to generate the most significant alphas as well as betas, given that they are developed based on the same time series for which their predictive power is tested. Therefore, it is not surprising that the 7 month static in-sample strategy has the highest alpha, which is statistically significant. However, Marquering & Verbeek (2004) mention that in-sample strategies often overstate out-of-sample predictability because of overfitting, finite sample biases and data snooping. The in-sample strategy thus confirms strong predictive ability, but cannot realistically simulate how an investor could trade on the information in real-time.

Regarding the out-of-sample static strategy, we observe that alpha is particularly high for trading on the 1 month horizon, but it is not statistically significant on the 5% level, although being just above that threshold. This suggests that an investor would not have generated abnormal returns using this strategy. However, the lack of significance could be the result of a shorter sample period of data regressed to find the intercept and coefficient used for predicting returns - potentially implying a less accurate approximation of the linear relationship.

With respect to the dynamic strategies, the rolling window strategy has a higher and more significant alpha for both the 1 and 7 month return horizons compared to the expanding window. However, alpha is only significant in the first half of the sample on the 7 month horizon, being the only realistically feasible trading strategy generating statistically significant four-factor alpha in the first half - indicating that an investor could have earned abnormal risk adjusted returns by following this strategy - translating to 9.16% on an annualized basis. Thereby, we can conclude that the more dynamic rolling window strategy is outperforming the expanding window strategy in the first half, and while the opposite is true in the second half - indicating that there are different characteristics of the strategies over time.

An important issue to consider is that transaction costs are not included in the excess return of the trading strategies. In comparison with only holding the benchmark index for the whole sample period (represented by *RMRF*), additional transaction costs have to be considered. This is partly due to that the strategy is assumed to change its position for each period which generates costs. In addition we use long-short strategies, as opposed to long-only strategy, which may imply increased transaction costs. To control for this, we used a transaction cost of 1%, which is classified as "high" according to Pesaran & Timmermann (1995). This effect was approximated by subtracting 1% from each period's return in the full sample and regressing Carhart four factors against the new returns. This resulted in an alpha of 3.14% instead of 4.14% for the 7 month in-sample static strategy, still being statistically significant.

6.2.3 Comparing the dynamic strategies' performance over time

When dividing the time series into two halves of equal length, we get two samples with different characteristics. For the first half, ranging between March 1998 and March 2008, we observe larger fluctuations of stock returns with higher realized volatility, as can be seen when comparing the variable's standard deviations in Table H2 and H3. The second half includes relatively smaller fluctuations, including the European sovereign debt crisis, with otherwise relatively steady increasing stock returns over time. Regarding the performance of the dynamic strategies, the rolling window strategy outperforms the expanding window strategy in the first half of the sample both with respect to 1 month and 7 months of stock returns, when considering both Sharpe ratio and risk adjusted returns in terms of higher alpha for the respective strategies. On the other hand, the expanding strategy clearly outperformed the rolling strategy in the second half of the dataset.

There is no clear reason for the initial outperformance and subsequent underperformance of the rolling strategy, but it could be related to the fact that stock returns were more volatile in the first half (23.2% and 18.0% standard deviation of excess returns for the first and second half of the dataset respectively for 7 month returns). This suggests that a more dynamic strategy (i.e. the rolling window strategy) is superior in generating abnormal returns when stock market volatility is higher, which is in line with Pesaran & Timmermann (1995), who suggest that the predictability of excess returns is larger at times when volatility is high, although there might not be a not a one-to-one relationship between abnormal returns and predictability.

Although the Sharpe ratio is higher in the first half for the rolling strategy in comparison with the expanding window strategy, it is still lower in comparison to excess market returns for the same period, indicating that a mean-variance investor who seeks to maximize his mean-variance efficient frontier would not prefer the strategy. Furthermore, the alpha for the rolling window strategy is generated when the stock market is experiencing a recession - indicating that the strategy is capable of predicting the bear market and profiting from it (seen in figure C). That ability is in line with findings in previous research, e.g. Chen (2008), showing that macroeconomic variables are particularly useful predictors of bear markets.

6.2.4 Strategy returns under a negative interest rate regime

When interest rates turn negative, the rolling window strategy is clearly performing worse in comparison with both its historical average performance as well as compared to other strategies, reflected in a 27 month period of consecutive negative returns starting in 2015. The inability to predict returns during the negative interest rate regime could be due to the less frequent changes in the repo rate during the past 12 months, making it harder to find a linear relationship between the change in repo rate and stock market returns. This indicates that the fixed linear relationship between lagged repo rate changes and stock returns used in the static strategies better predicts stock returns when there is a negative interest rate regime, as opposed to the dynamic rolling window strategy that continuously re-estimates the same linear relationship and fails to predict returns during this period (see graph H4). This also seems to be consistent with the fact that the rolling window strategy has a positive and statistically significant four-factor alpha of 5.25% (translating to 9.16% annually) in the first half, while having a negative and insignificant alpha in the second, less volatile half of the dataset.

Furthermore, the static strategies and the expanding window strategy seem to perform relatively well during the last years of the time series in terms of Sharpe ratio (can be seen in table H3). Towards the end of the time series, the expanding window strategy's beta becomes increasingly similar to the static in-sample trading strategy, since it is regressed using almost the same time window (except for the subsequent periods which only are included in the in-sample strategy's window). The similar betas explain that the expanding window strategy becomes more of a static strategy towards the end as a larger time series is regressed.

6.2.5 Linking strategy returns to macroeconomic phenomena

To connect the statistical observations with reality, the inability for the rolling window strategy to predict stock returns under a negative interest rate regime may in turn be related to the relationship between changes in repo rate and inflation. As documented by Panizza & Wyplosz (2016), there is a claimed decreasing effectiveness of interest rates as a monetary policy tool internationally - in Sweden characterized by the fact that inflation has remained below the target for a prolonged period of time despite a low and even negative repo rate (*How monetary policy affects inflation,* Sveriges Riksbank, 2018). This could potentially translate into less frequent and/or delayed changes (increases) of the repo rate by the central bank to avoid the risk of inhibiting inflation, which would in turn be translated into difficulties for a rolling regression model to predict stock returns based on the linear relationship between lagged changes in the repo rate and stock returns. However, deeper and more extensive research has to be conducted to confirm the economic causality between repo rate changes and stock market returns.

7 Conclusion

This thesis investigates whether certain macroeconomic variables have predictive power with respect to Swedish stock returns and if an investor can generate abnormal returns using macroeconomic variables. Predictive power is affirmed for changes in the repo rate and changes in the exchange rate, confirming findings in previous research on macroeconomic variables' predictive power. The results imply that changes in the repo rate impacts future stock returns negatively and that currency depreciation negatively affects future stock returns, which is line with previous international findings.

An investor constructing his portfolio with the aim of certain four-factor exposure would have benefited from the positive statistically significant, annualized four-factor alpha of 9.16% generated by the dynamic rolling window strategy in the first half of the time series - providing evidence that it has been historically possible to generate risk-adjusted abnormal returns using macroeconomic variables, when not considering transaction costs (which would partly reduce the abnormal return). However, the recent poor performance of the rolling dynamic strategy is at the same time suggesting issues with the model, and thereby we conclude that it is unlikely that an investor can generate abnormal returns going forward, given the prevailing negative interest rate environment.

When interest rates turn negative and changes in the repo rate are less frequent, the rolling window strategy is sharply underperforming other strategies. Thereby, the fixed linear relationship between lagged repo rate changes and stock returns used in the static strategies better predict stock returns when there is a negative interest rate regime, as opposed to the dynamic rolling window strategy that continuously re-estimates the same linear relationship over a rolling 12 month period. Further analysis suggests that the performance of the rolling window trading strategy is affected by the effectiveness of the repo rate as a monetary policy tool, forcing the repo rate to remain at extraordinary low levels due to its recent inability to stimulate inflation.

Our analysis brings relevant implications for portfolio managers in terms of how stock index returns can be predicted using methods based on macroeconomic variables that have previously not been explicitly used in the Swedish stock market. In turn, the findings considering the first difference in repo rate further provides insights for policy makers with respect to potential side effects of using the repo rate as a monetary policy tool, given its significant impact on stock returns. Also, it gives an idea of how investors can exploit the predictive power and use it to construct trading strategies, as well as the advantages and caveats of different regression based trading strategies using individual macroeconomic variables.

8 Limitations and suggestions for further research

The purpose of the thesis is to explore the explanatory power of macroeconomic variables on a general basis and not other potential variables that might explain the stock market such as traditional financial ratios, correlations with other international markets or other variables. We limit this paper to evaluation of macroeconomic variables' significance in forecasting, as opposed to constructing a forecasting model and assessing its predictive power. Thus, the R-squared value in the linear regression is not maximized, but the significance of individual variables is focused on instead. Including financial ratios together with the macroeconomic variables with significant predictive ability in this paper, as well as in other papers referred to, would thereby be an interesting area to further examine - to increase the R-squared value in a predictive regression. Also, while the statistical causality can be determined through the tests undertaken, it does not provide an answer that explain economic causality.

Throughout this paper, the predictive power of the change of the repo with respect to OMXS30 stock returns is investigated. This is something that has to be considered by the Swedish central bank that decides the repo rate, given that it is used as a tool to create a certain economic environment in Sweden. However, to be able to make decisions based on the probable effects on stock returns, it would be interesting, and contribute with added value to the discussion if investigating what factors in the economy that OMXS30 return in turn can predict. Particularly, this topic is interesting since the prevailing negative interest rate environment might lead to a structural break which could disrupt current forecasting models used by both policy makers and investors.

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10 Appendix

TABLE A

DICKEY FULLER TEST FOR UNIT ROOT				
	H_0: the variable contains a unit root			
		Interpolated Dickey-Fuller		
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Return	-13.475	-3.464	-2.881	-2.571
dRepo	-7.484	-3.464	-2.881	-2.571
Inflation	-15.349	-3.464	-2.881	-2.571
gPVI	-16.945	-3.464	-2.881	-2.571
dTCW	-12.283	-3.464	-2.881	-2.571
gMS	-18.913	-3.464	-2.881	-2.571
dSlope	-11.262	-3.464	-2.881	-2.571

MacKinnon approximate p-value for Z(t) = 0.0000

Note: The p-value is applicable for all variables. Being able to reject H_0 implies that the data is stationary

TABLE B

BREUSCH-PAGAN /COOK-WEISBERG TEST FOR HETEROSKEDASTICITY		
	H_0: constant variance	
	chi2 (1)	Prob > chi2
ReturnFW1	0.70	0.4041
ReturnFW7	6.90	0.0086

TABLE C1

CORRELATION TABLE						
	The correlation between all independent variables used in the regressions are presented below					
	dRepo	Inflation	gPVI	dTCW	gMS	dSlope
dRepo	1.0000					
Inflation	0.1979	1.0000				
gPVI	0.1050	0.2663	1.0000			
dTCW	-0.2355	-0.1260	0.0118	1.0000		
gMS	-0.1400	-0.1640	0.2219	0.0963	1.0000	
dSlope	-0.3417	-0.1088	0.0681	0.1692	0.0295	1.0000

TABLE C2

VARIANCE INFLATION FACTOR TEST		
	VIF factors are displayed below, used for testing for multicollinearity between the independent variables	
	VIF	1/VIF
dRepo	1.24	0.806
gPVI	1.20	0.832
Inflation	1.18	0.847
dSlope	1.17	0.856
gMS	1.14	0.876
dTCW	1.08	0.925
Mean VIF	1.17	

Note: VIF < 10 indicates no multicollinearity, in accordance with e.g. Neter et al. (1996)

TABLE D

DURBIN-WATSON TEST FOR AUTOCORRELATION	
	> 2 = negative autocorr. 2 = no autocorr. < 2 = positive autocorr.
	Durbin-Watson d-statistic
regresid_lag1	1.844
regresid_lag7	0.338

Note: The tests are conducted on the residuals of each of the regressions conducted on 1 and 7 months future stock returns using the macroeconomic variable

TABLE E

JARQUE-BERA NORMALITY TEST		
	H_0: Normally distributed residuals	
	chi2	Prob > chi2
regresid_lag1	24	6.2e-06
regresig_lag7	13.5	0.0012

Note: The tests are conducted on the residuals of each of the regressions conducted on 1 and 7 months future stock returns using the macroeconomic variable

TABLE F

	SELECTION ORDER CRITERIA							
	The Akaike Information Criterion (AIC) and Schwarz Bayesian Information Criterion (SBIC) are used to determine the number of lags that are to be investigated in the VAR model and the Granger causality test							
lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-2233				0.806	19.649	19.692	19.754
1	-2060.01	345.98	49	0	0.272	18.562	18.901*	**19.404***
2	-2008.54	102.94	49	0	0.266	18.540	19.177	20.119
3	-1946.01	125.06	49	0	0.237	18.421	19.356	20.738
4	-1860.30	171.44	49	0	0.173	18.099	19.331	21.152
5	-1793.61	133.37	49	0	0.149	17.944	19.473	21.734
6	-1740.50	106.21	49	0	0.146	17.908	19.735	22.435
7	-1674.08	132.84	49	0	0.128*	**17.755***	19.879	23.020
8	-1640.47	67.23	49	0.043	0.150	17.890	20.311	23.891
9	-1609.82	61.284	49	0.112	0.182	18.051	20.770	24.790
10	-1563.58	92.49*	49	0	0.194	18.075	21.091	25.551

Endogenous: Return dRepo Inflation gPVI dTCW gMS dSlope
Exogenous: _cons

Note: Both the dependent and independent variables are set as endogenous since the VAR model and Granger causality test (which the lags suggested above will be used for) examines the causal lagged relationship between all variables

TABLE G1

REGRESSION ON 1 MONTH FUTURE STOCK RETURNS USING THE MACROECONOMIC VARIABLES						
	Predictive regression on stock returns 1 month ahead					
ReturnFW1	*Coef.*	*Std.Err*	*t*	*P > t*	*[95% Confidence Interval]*	
dRepo	-5.662	2.675	-2.12	0.035*	-10.931	-0.392
Inflation	-1.719	0.981	-1.75	0.081	-3.652	0.214
gPVI	0.049	0.033	1.51	0.132	-0.015	0.114
dTCW	-0.295	0.284	-1.04	0.300	-0.855	0.265
gMS	0.112	0.294	0.38	0.705	-0.468	0.691
dSlope	*-4.366*	*2.781*	*-1.57*	*0.118*	*-9.846*	*1.113*
_cons	*0.321*	*0.424*	*0.76*	*0.450*	*-0.515*	*1.156*
	Number of observations		*238*	*R-squared*		*0.0459*
	F(6, 231)		*1.85*	*Adjusted R-squared*		*0.0212*
	Prob > F		*0.0000*	*Root MSE*		*5.6639*

*p-value < 5% **p-value < 1% ***p-value < 0.1%

TABLE G2

REGRESSION ON 7 MONTHS FUTURE STOCK RETURNS USING THE MACROECONOMIC VARIABLES						
	Predictive regression on stock returns 7 months ahead					
ReturnFW7	*Coef.*	*Newey-West Std.Err*	*t*	*P > t*	*[95% Conf. Interval]*	
dRepo	-41.991	7.528	-5.58	0.000***	-56.824	-27.157
Inflation	-7.568	3.152	-2.40	0.017*	-13.779	-1.358
gPVI	0.201	0.091	2.21	0.028*	0.022	0.380
dTCW	-0.693	0.738	-0.94	0.349	-2.148	0.762
gMS	-0.573	0.853	-0.67	0.502	-2.254	1.108
dSlope	-1.551	8.422	-0.18	0.854	-18.148	15.046
_cons	2.682	1.608	1.67	0.097	-0.486	5.850
	Number of observations		*232*	*R-squared*		-
	F(6, 225)		*7.12*	*Adjusted R-squared*		-
	Prob > F		*0.0000*	*Root MSE*		-

*p-value < 5% **p-value < 1% ***p-value < 0.1%

Note: This regression produces Newey-West standard errors, for which the error structure is assumed to be heteroskedastic and autocorrelated. No R-squared, adjusted R-squared nor root MSE values are generated

TABLE H1

DESCRIPTIVE STATISTICS OF THE TRADING STRATEGIES						
	Descriptive statistics for the return of all trading strategies' excess returns and the stock market excess returns at 1 and 7 month horizons					
	Obs.	Mean	Std.Dev	SR	Min	Max
RMRF7m	220	6.214	20.836	0.298	-41.881	64.829
InStatRepo7m	219	6.027	19.405	0.311	-45.924	72.082
OutStatRepo7m	99	6.547	14.376	0.455	-37.734	46.046
RollRepo7m	201	0.912	18.585	0.049	-40.489	73.049
ExpRepo7m	210	0.997	20.418	0.049	-45.924	72.082
RM_RF_montly	227	0.689	5.754	0.120	-18.153	21.638
InStatRepo1m	225	0.857	5.848	0.147	-15.595	19.898
OutStatRepo1m	105	1.257	4.896	0.257	-14.989	19.898
RollRepo1m	213	0.634	5.816	0.109	-14.593	19.898
ExpRepo1m	222	0.087	5.943	0.015	-15.102	19.898

Note: All results are presented in percentage, e.g. the RMRF7m has an average return of 6.214%. Due to that the Carhart four factors only are available on a monthly basis until January 2017, the regression is only conducted using data until that date

TABLE H2

DESCRIPTIVE STATISTICS OF THE FIRST HALF OF THE TRADING STRATEGIES

Descriptive statistics for the return of all trading strategies' excess returns and the stock market excess returns at 1 and 7 month horizons between March 1998 and March 2008

	Obs	Mean	Std.Dev	SR	Min	Max
RMRF7m	114	6.070	23.210	0.262	-40.634	64.829
InStatRepo7m	113	4.869	22.804	0.214	-45.924	72.082
OutStatRepo7m	0					
RollRepo7m	95	2.644	21.115	0.125	-40.489	73.049
ExpRepo7m	104	-4.110	23.429	-0.175	-45.924	72.082
RM_RF_monthly	121	0.526	6.280	0.084	-15.381	15.951
InStatRepo1m	119	0.543	6.585	0.083	-15.595	17.280
OutStatRepo1m	0	-	-	-	-	-
RollRepo1m	107	1.041	6.515	0.160	-14.593	17.645
ExpRepo1m	116	-0.719	6.661	-0.108	-15.102	17.645

Note: All results are presented in percentage, e.g. the RMRF7m has an average excess return of 6.214%. Due to that the Carhart four factors only are available on a monthly basis until January 2017, the regression is only conducted using data until that date. However, the data is split between March 2008 and April 2008 since the regressions conducted on the static out-of-sample trading strategy begins in March 2008. Hence, no statistics are available for the static out-of-sample strategy during the first half

TABLE H3

DESCRIPTIVE STATISTICS OF THE SECOND HALF OF THE TRADING STRATEGIES

Descriptive statistics for the return of all trading strategies' excess returns and the stock market excess returns at 1 and 7 month horizons between April 2008 and January 2017

	Obs	Mean	Std.Dev	SR	Min	Max
RMRF7m	106	6.370	18.046	0.353	-41.881	53.855
InStatRepo7m	106	7.261	14.969	0.485	-37.734	46.134
OutStatRepo7m	99	6.547	14.376	0.455	-37.734	46.046
RollRepo7m	106	-0.641	15.926	-0.040	-35.787	50.839
ExpRepo7m	106	6.008	15.500	0.388	-37.734	46.134
RM_RF_montly	106	0.875	5.110	0.171	-18.153	21.638
InStatRepo1m	106	1.209	4.897	0.247	-14.989	19.898
OutStatRepo1m	105	1.257	4.896	0.257	-14.989	19.898
RollRepo1m	106	0.224	5.010	0.045	-14.593	19.898
ExpRepo1m	106	0.968	4.924	0.197	-14.989	19.898

Note: All results are presented in percentage, e.g. the RMRF7m has an average excess return of 6.214%. Due to that the Carhart four factors only are available on a monthly basis until January 2017, the regression is only conducted using data until that date. However, the data is split between March 2008 and April 2008 since the regressions conducted on the static out-of-sample trading strategy begins in March 2008

TABLE H4

DESCRIPTIVE STATISTICS OF THE LAST TWO YEARS OF THE TRADING STRATEGIES						
	Descriptive statistics for the return of all trading strategies' excess returns and the stock market excess returns at 1 and 7 month horizons between January 2015 and January 2017					
	Obs	Mean	Std.Dev	SR	Min	Max
RMRF7m	25	6.715	10.816	0.621	-12.712	24.543
InStatRepo7m	25	1.613	12.150	0.133	-16.219	22.404
OutStatRepo7m	25	1.613	12.150	0.133	-16.219	22.404
RollRepo7m	25	-3.919	11.102	-0.353	-18.547	19.990
ExpRepo7m	25	1.613	12.150	0.133	-16.219	22.404
RM_RF_montly	25	0.880	4.212	0.209	-7.136	8.064
InStatRepo1m	25	0.279	4.241	0.066	-7.091	7.454
OutStatRepo1m	25	0.279	4.241	0.066	-7.091	7.454
RollRepo1m	25	-0.578	4.199	-0.138	-7.091	7.454
ExpRepo1m	25	0.279	4.241	0.066	-7.091	7.454

Note: All results are presented in percentage, e.g. the RMRF7m has an average excess return of 6.214%.

TABLE I1

REGRESSIONS ON THE FIRST AND SECOND HALF OF THE 1 MONTH DYNAMIC TRADING STRATEGIES USING THE CARHART FOUR FACTORS				
	Regression on the trading strategies' excess returns when predicting stock market excess returns for the following month between March 1998 - March 2008 and April 2008 - January 2017 respectively			
	March 1998 - March 2008		April 2008 - January 2017	
	ExpRepo1m	RollRepo1m	ExpRepo1m	RollRepo1m
RM_RF_monthly	0.355**	0.161	0.164	-0.235*
	(3.26)	(1.49)	(1.57)	(-2.18)
HML_vw	-0.111	-0.0694	-0.0158	-0.122
	(-1.10)	(-0.72)	(-0.09)	(-0.67)
SMB_vw	-0.0337	0.131	-0.254*	-0.147
	(-0.31)	(1.29)	(-2.03)	(-1.14)
MOM_vw	0.281***	0.370***	-0.0579	0.137
	(4.28)	(6.00)	(-0.48)	(1.11)
_cons	-0.92	0.876	0.666	0.328
	(-1.61)	(1.59)	(1.43)	(0.68)

*p-value < 5% **p-value < 1% ***p-value < 0.1%

Note: The values in the parentheses are the test statistics, and the other values are the beta exposure to each portfolio. All portfolios are value weighted. Due to that the Carhart four factors only are available on a monthly basis until January 2017, the regression is only conducted using data until that date

TABLE I2

REGRESSIONS ON THE FIRST AND SECOND HALF OF THE 7 MONTHS DYNAMIC TRADING STRATEGIES USING THE CARHART FOUR FACTORS

	Regression on the trading strategies' excess returns when predicting stock market returns for the next 7 months between March 1998 - March 2008 and April 2008 - January 2017 respectively			
	March 1998 - March 2008		April 2008 - January 2017	
	ExpRepo7m	RollRepo7m	ExpRepo7m	RollRepo7m
RMRF7m	0.008 (0.07)	-0.0026 (-0.02)	0.237** (2.850)	0.010 (0.110)
HML7m	-0.422*** (-4.80)	-0.339*** (-4.08)	0.284 (1.440)	-0.413 (-1.92)
SMB7m	0.289* (2.30)	0.00432 (0.03)	-0.297* (-2.49)	-0.057 (-0.43)
MOM7m	-0.0928* (-2.01)	0.330*** (7.78)	-0.0592 (-0.48)	0.273* (2.01)
_cons	-0.812 (-0.38)	5.246** (2.64)	1.933 (1.18)	-0.838 (-0.47)

*p-value < 5% **p-value < 1% ***p-value < 0.1%

Note: The values in the parentheses are the test statistics, and the other values are the beta exposure to each portfolio. All portfolios are value weighted. Due to that the Carhart four factors only are available on a monthly basis until January 2017, the regression is only conducted using data until that date

FIGURE A

OMXS30 AND RETURN DEVELOPMENT OVER TIME

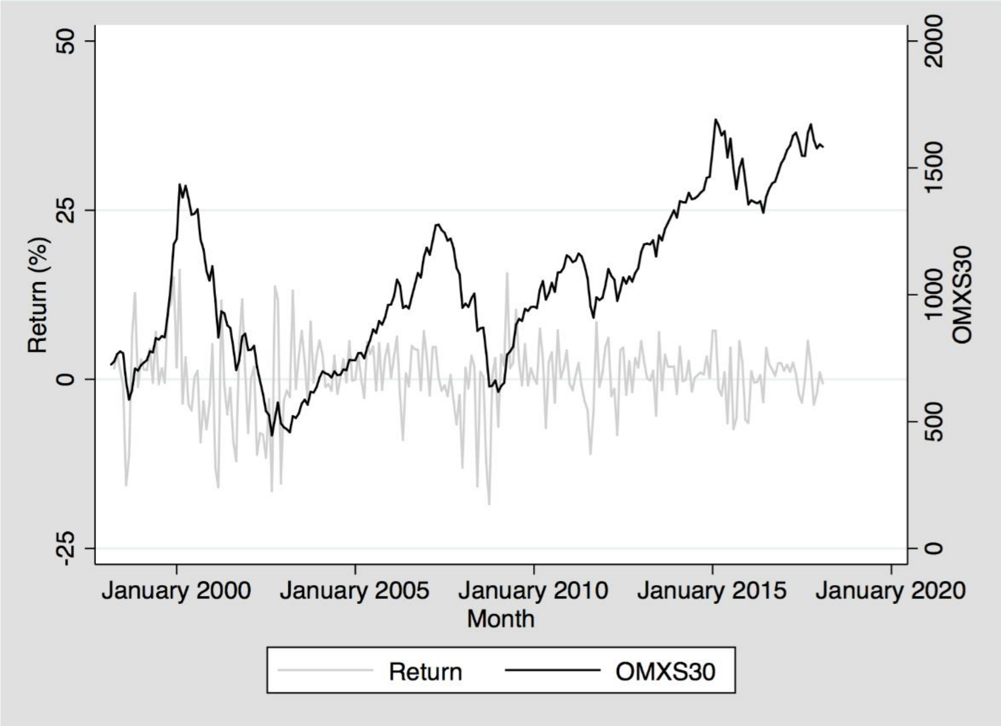

FIGURE B1

RESIDUALS FROM THE REGRESSION ON 1 MONTH FUTURE STOCK RETURNS

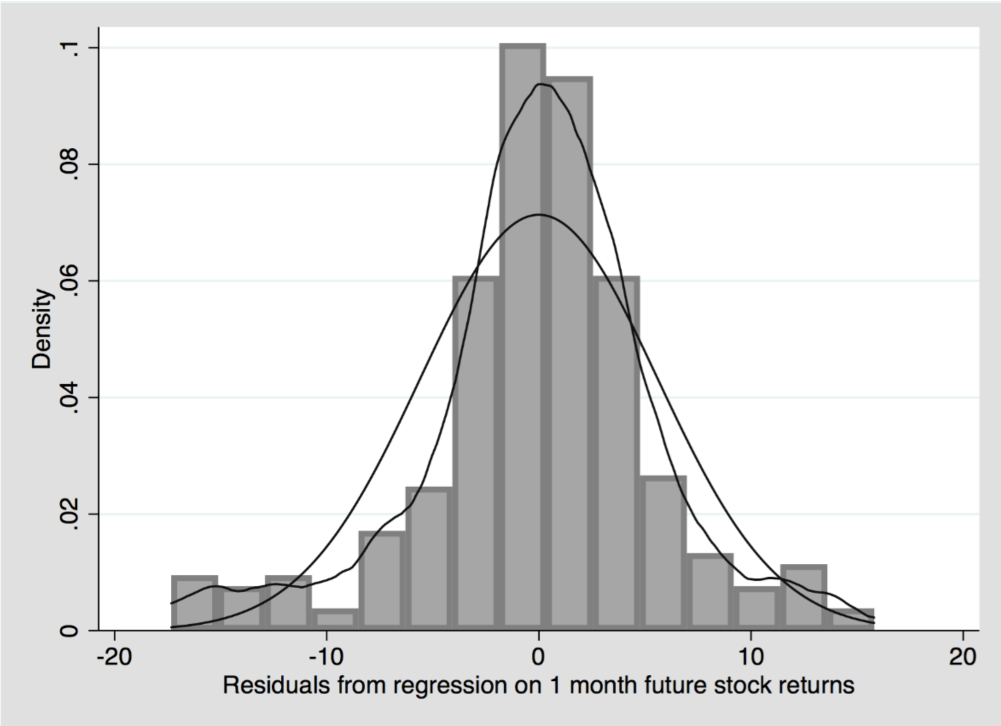

FIGURE B2

RESIDUALS FROM THE REGRESSION ON 7 MONTH FUTURE STOCK RETURNS

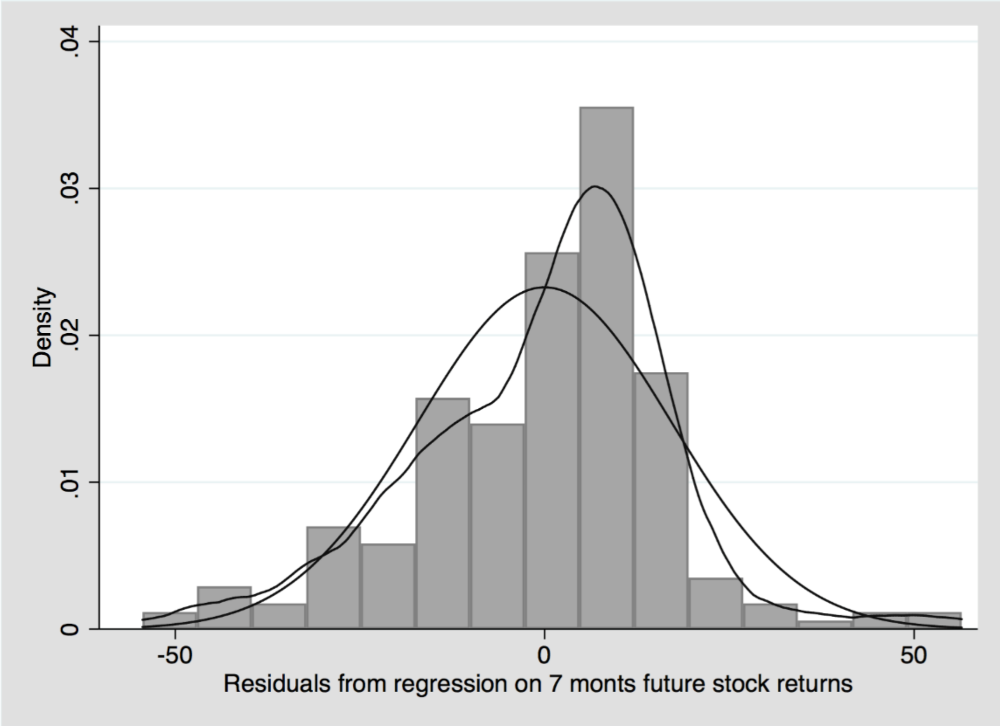

FIGURE C

DEVELOPMENT OF THE ROLLING WINDOW 7 MONTH STRATEGY AND EXCESS MARKET RETURNS