

# LUND UNIVERSITY

## MASTER THESIS

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### **PREDICITING BULL AND BEAR IN THE SWEDISH STOCK MARKET**

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### **Abstract**

Very little if any previous research has been done on the potential predictability of bear and bull regimes in the Swedish stock market. In this study my aim is to predict OMXS30 bull and bear regimes with dynamic binary time series models. After using a nonparametric approach to identify the regimes of bull and bear periods in the market I looked at both an in sample and out of sample test. Based on monthly data I found different predictive variables, with the variables with highest predictive power being, the term spread and market liquidity deviation. Further variables with statistically significant results and predictive power are, the federal fund rate, purchasing manager index and the nominal return. The result can be improved using the dynamic structure in the binary response model. Using multivariate dynamic binary time series I found that the model yield higher returns than the buy and hold strategy.

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Keywords: Market liquidity deviation, Dynamic, Bear markets, State, Conditional probability, Probit model

I want to thank Joakim Westerlund for guiding me and directing me in my quest for knowledge.

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# 1 INTRODUCTION

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*“Buy cheap and sell dear” (Benjamin Graham 1949)*

In his book the Intelligent Investor Graham described two ways in which the intelligent investor might look for superior returns: the way of timing and the way of pricing. In discussing timing he meant the “endeavor to anticipate the action of the stock market”. He was talking about the fact of buying when the future course is deemed to be upward and to sell or refrain from buying when the course is downward. In pricing he meant the “endeavor to buy stocks when they are quoted below their fair value and to sell them when they rise above such value”. Even though he warned from trying to time the market, it will be the focal point of this paper.

A lot of attention has been paid to the documentation of many features of returns in equity markets. It has for example been shown that returns show a range of features such as an equity premium, volatility clustering, fat tailed densities and more (Pagan 1996). There has also been a great deal of research done in predicting stock market returns. At date we have many documented violations of the market efficiency theory. For example,

*“Several predetermined variables that reflect levels of bond and stock prices appear to predict returns on common stocks of firms of various sizes, long term bonds of various defaults risks and default free bonds of various maturities” (Keim and Stambaugh, 1986)*

A well-known paper is one where Pontiff and Schall (1998) show one can predict returns using book to market ratio. Others have shown that there is predictive power also of dividend yield and the earnings-price ratio (Lewellen, 2004). But it is not only financial variables that have been used to predict stock market movements, but there have also been empirical studies showing that using macro variables such as interest rates, inflation, unemployment rates and money stock can have predictive power (Chen, 2009).

Recent studies are instead focusing on trying to predict different regimes in the stock market. The so called bull and bear markets are an extensive period of time when stock returns are rising or falling. This paper will extend the research and try to predict the bull and bear markets using a dynamic binary probit model.

Since the financial crisis of 2008 the interest in trying to predict the likelihood of the next financial crisis has been growing, for obvious reasons. Central bankers, private forecasters, investors and business professionals want to know which indicators that provide reliable forecasts of stock market turning points. The benefits are in helping market participants earn more returns by a market timing strategy rather than a simple buy and hold strategy, but also in helping policy makers. There has

been research on momentum trading and in a paper Asem and Tian (2010) conclude that:

*“Following UP markets, momentum profits are higher when the markets continue in the UP state than when they transition to DOWN states, suggesting that the profits following UP markets are mainly due to the profits when the markets continue. Following DOWN markets, we document both large momentum profits when the markets continue in DOWN states and large losses when markets transition to UP states”*

Bear market prediction isn't much different from business cycle prediction trying to identify recession and expansion periods of real economic activity. Trying to measure transitions from recessions and expansions has long been a major focal point for business cycle research. The idea in this paper is using their ideas and trying to do the same on stock market regimes of bear (recession) and bull (expansion).

Although bull and bear market are common words in an investors dictionary there does not exist any academic consensus on the definition. Instead academics have been using different ways in which they capture the bull and bear movements in the market.

The most popular methods is the parametric Markov switching method model, but recently there has been evidence of better results using the non-parametric binary autoregressive probit model based on the well-known Bry-Boschan (1971) algorithm is superior to a simple two state Markov model. (Chen 2009 and Seidl 2012). Though it is not in the interest of this thesis to compare the Markov switching method and the binary method, I will give a short description of the Markov switching approach.

To the best of my knowledge there is no paper implementing a binary probit model on the Swedish stock market using state variable as the dependent variable. The static has many drawbacks as in the lack of dynamics to capture how bear markets probability is influenced by the past probabilities. Therefore I will also look at the dynamic model, there is also proof of the latent autoregressive model have good predictive power, this I will leave to future research.

My inspiration for the paper is mainly driven from Chen (2009) Pagan and Sossounov (2003) and Nyberg (2013), but I also use inspiration from recession prediction papers like Kauppi and Saikkonen (2008) and Moneta (2005). Chen use the probit model in trying to predict the different regimes. He does this by using just one variable with one lag at the time in trying to find the best predictive variable at the best lag. He conclude that the term spread has the highest predictive power in predicting states on the S&p500.

Nyberg extends this approach in looking at a multivariate probit model. He concludes that a multivariate probit model with dynamics and autoregressive variables are superior to just the static model.

Moneta finds that yield spread between the ten year government bond rate and the 3 month interbank rate outperforms all other spreads in predicting recessions in the euro area. Pagan and Sossounov outlines a way of

defining bull and bear market, it's their definition I will use in drawing out the bull and bear states. Kauppi and Saikkonen outlines some extensions to the usual static probit models that I will present in my method section.

The remainder of this paper is structured as follows. Section 2 I will take a closer look at the Bry and Bosch algorithm and its dating method and make a short description of the Markov model. I will also present the data and models used in this paper. In section 3 I will present the results from my different probit models. Section 4 round up this paper with a short discussion on the results, and suggestions for further research.

## 2 METHOD AND DATA

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Suppose we have our binary time series model, where the dependent variable  $s_t$ ,  $t=1, 2, \dots, T$  is a realization of a stochastic process that only again takes on the values 1 or 0 at time  $t$ . As defined in eq. (9), the value one ( $s_t=1$ ) is a bull market and the value zero ( $s_t=0$ ) is a bear market. We are interested in modeling  $s_t$  using  $x_t$  which is a matrix of explanatory variables.

### 2.1 METHOD AND MODEL

Denoting the conditional expectation of  $s_t$  by  $E_{t-1}(s_t)$ , conditional on the information included in the information set  $\Omega_{t-1}$  at time  $t-1$ , the conditional probability of the bull market at time  $t$  can be written as:

$$p_t = E_{t-1}(s_t) = P_{t-1}(s_t = 1) = \Phi(\pi_t) \quad (1)$$

In practice, one typically assumes that  $\Phi$  is the CDF cumulative distribution function of either a standard normal distribution or a logistic distribution. The former is the probit model and the latter is the logit model. In my empirical application the probit model is used. This ensure that  $\Phi(\pi_t)$  takes values in the unit interval  $(0, 1)$ , giving us a probability of a bull market. The probability of a bear market is simply  $P_{t-1}(s_t = 0) = 1 - p_t$ . In eq. (1)  $\pi_t$  is a linear function of the different explaining variables included in the information set. Chen (2009) used the classical static probit model, which will also be our starting point looking at the data. The static model can be written as:

$$\pi_t = \omega + x'_{t-h}\beta \quad (2)$$

Where  $x_{t-h}$  is a matrix of the explanatory variables. The index  $h$  determines the forecast horizon. This is a static model since the explanatory variables in  $x$  have an  $h$ -period lagged effect on the conditional probability. Looking instead on much used dynamic model we get:

$$\pi_t = \omega + \delta s_{t-1} + x'_{t-h}\beta \quad (3)$$

You could of course just include the lagged state variable in the  $x_{t-h}$  matrix. There are a couple of ways in which eq. (3) can be extended. I choose to look at one extension used in Kauppi and Saikkonen (2008). The model can be written as:

$$\pi_t = \omega + \beta x_{t-h} + \gamma s_{t-1} x_{t-h}. \quad (4)$$

This extension haven't been used in trying to predict bull and bear markets before to the best of my knowledge. This is based on the idea that the impact of the explanatory variables may depend on a lagged value of the binary variable  $s_t$ . For instance, the impact of the term spread on the bull

indicator may differ (be asymmetric) during bull and bear periods and this may give a better model that is advantageous in forecasting.

The parameters can be estimated using maximum likelihood (ML).

## 2.2 FORECASTING PROCEDURES

I will follow the forecasting procedures set out by Nyberg (2013) and Kauppi and Saikkonen (2008). When looking at the general model, an optimal h-month forecast of  $s_t$  based on set  $\Omega_{t-h}$ , is the conditional expectation  $E_{t-h}(s_t)$ . Again turning our attention to eq. (1), using the law of iterated conditional expectations we get:

$$E_{t-h}(s_t) = E_{t-h}(P_{t-1}(s_t = 1)) = E_{t-h}(\Phi(\pi_t)) \quad (5)$$

Now depending on the model employed, the relation mentioned above will lead to different forecasting procedures to obtain h-period forecasts for the state of the stock market.

The benchmark forecast are obtained from the static binary probit model, where eq. (2) is just plugged in to the expression in eq. (5). In practice one might choose where  $k \geq h$ , h is the forecast horizon. The reason for doing this is because then the value used of the variable is known at the time forecasting Kauppi and Saikkonen (2008).

The forecasts gets more complicated when I introduce the lagged state variable ( $s_{t-1}$ ), now we have a dynamic probit model like in eq. (3). One approach in forecasting this is the iterative multiperiod forecasting approach. This model can be written like:

$$E_{t-h}(s_t) = E_{t-2}(\Phi(\omega + \delta s_{t-1} + x'_{t-k}\beta)) \quad (6)$$

This expression is holding the unknown value of  $s_{t-1}$  on the right hand side. The binary nature of  $s_t$  makes it possible for us to compute forecast eq. (6) using clear formulae by accounting for the two possible paths between  $s_{t-2}$  and  $s_t$ . Now considering h=2 we get the following equation:

$$E_{t-2}(s_t) = \sum_{s_{t-1} \in \{0,1\}} P_{t-2}(s_{t-1}) \Phi(\omega + \delta s_{t-1} + x'_{t-k}\beta) \quad (7)$$

where

$$P_{t-2}(s_{t-1}) = \Phi(\omega + \delta s_{t-2} + x'_{t-k}\beta)^{s_{t-1}} * [1 - \Phi(\omega + \delta s_{t-2} + x'_{t-k}\beta)]^{1-s_{t-1}}$$

This is the solution derived iteratively by accounting for two possible values of  $s_{t-1}$  and their conditional probabilities. Using h>2 the expression explodes since the number of paths between t-h and t is larger and the situation gets more complicated. For this reason I will focus on h=2.

## 2.3 DEPENDENT VARIABLE, DEFINING BULL AND BEAR

In looking at bull and bear regimes the point is that there are a prolonged period of either decreasing or increasing market prices. Comparing this to regular business cycle it is just as if we are trying to predict a recession or expansion in the economy. In using a regime switching model we are essentially trying to capture a predictive behavior in stock markets. It's as if the aggregate mood of the participants in the market goes from positive to negative.

### 2.3.1 Markov switching model

As mentioned in the introduction most of the regime switching models are Markov switching models, where the regimes are unobserved and controlled by a Markov chain. Let  $r_t = \Delta \log P_t$  be stock returns, simple two state Markov switching model of stock returns can be written in the following way:

$$r_t = \mu_{st} + \varepsilon_t; \varepsilon_t \sim i.i.d. N(0, \sigma_{st}^2) \quad (7)$$

Where  $\mu_{st}$  and  $\sigma_{st}^2$  are the state dependent mean and variance of  $r_t$ . The state is just a latent dummy variable where 1 means bull and 0 means bear. The probabilities for transitions between states are assumed to be fixed and are given by a transition matrix.

$$P = \begin{bmatrix} p^{00} & 1 - p^{00} \\ 1 - p^{11} & p^{11} \end{bmatrix} \quad (8)$$

Where

$$p^{00} = P(s_t = 0 | s_{t-1} = 0)$$

$$p^{11} = P(s_t = 1 | s_{t-1} = 1)$$

Then after the two unobserved regimes have been statistically identified, the filtered probabilities are computed. This is just a brief explanation since the Markov model isn't the focus of my paper (Privault 2013).

### 2.3.2 A Nonparametric approach

The key feature in the nonparametric approach is using dating algorithms for locating the turning points (peaks and troughs) that are the local maxima and minima of the series. I follow the settings in Pagan and Sossounov (2003) with slight differences. This is to identify a peak (or trough) in the stock market when  $r_t$  reaches a local maximum or minimum. The window for this will be six, used by Chen (2009) using the monthly Bry-Boscan algorithm. A local peak occurs at time  $t$  whenever  $\{r_t > r_{t \pm 6}\}$  and for a local trough  $\{r_t < r_{t \pm 6}\}$ . Once the turning points are obtained, the peak to trough period will be seen as the bear period ( $s_t=0$ ) while the trough to peak period are identified as the bull period ( $s_t=1$ ).

Throughout this paper the value one signifies a bull market and the value zero denotes a bear market.

$$s_t = \begin{cases} 1, & \text{a bull market at time } t \\ 0, & \text{a bear market at time } t \end{cases} \quad (9)$$

So if we can predict the state in eq. (9) we should be able to some extent predict our stock return. I will show how the turning points of the stock market can be extracted in real time from a realized stock returns using Bry and Boschan dating rule. As you will see later just because we are in a bull (bear) market that in itself doesn't rule out the possibility that the monthly stock return is negative (positive).

### 2.3.3 The Bry and Boschan dating rule

Before we can look at the two different states we need to set up rules that set the states apart from each other. As mentioned before even though market participants have for a long time thought about the market as being in different states there has never been a clear consensus on what a bull and bear market is. Chauvet and Potter (2000) describes it as "in stock market terminology, bull (bear) market corresponds to periods of generally increasing (decreasing) market prices".

One possible idea is using the "naive" moving average (Chen 2009), which says if the stock return is above the average it's a bull market, and the turning point is when the return instead turns below the average for two consecutive months. Another adjustment is using the sharpe ratio, where if the sharp ratio goes below the average for two consecutive months we have a bear market.

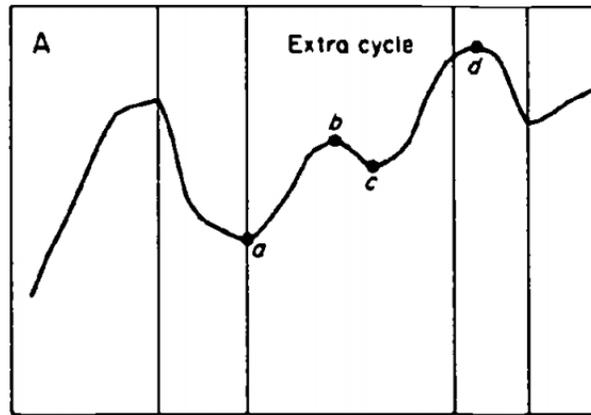
In this paper I will use Pagan and Sossounov (2003) definition and in doing so I will turn to the mechanical nonparametric approach based on Bry and Boschan turning points. The reason for this is that in his paper Seidl (2012) found that the regime switching algorithm improves the performance of the optimal portfolio. The objective of this paper is not to describe the entire book by Bry and Boschan (1971) instead I will try to explain the most important parts of it.

*"After specific cycles have been identified, it is still necessary to pinpoint specific peaks and troughs. This may raise a large number of questions, some of which have to be answered on the basis of rules which, though occasionally arbitrary, are needed in order to ensure consistency of treatment."* (Bry and Boschan 1971)

In this quote we get a better grasp of the thinking in forming the rules, it is basically a pattern recognition program that seeks to isolate the patterns using a sequence of rules. Using Pagan and Sossounov (2003), one part is in using a criterion for deciding on the location of the potential peaks and troughs. This is again done by setting a rule giving  $\{r_t < r_{t \pm 6}\}$  and  $\{r_t > r_{t \pm 6}\}$ . Second you try to look at the durations between the peaks and troughs and then use a couple of censoring rules in trying to restrict the minimal length of any phase and those of complete cycles.

In choosing my rules I looked at Nyberg (2013) and Pagan and Sossounov (2003) and also Chen (2009), but all of them used rules adjusted to different indexes in the USA, so I used a combination of their rules that seem to give a better fit for Swedish OMXS30. I choose the minimum time spent in a bull (time from trough to next peak) or bear (time from peak to next trough) to be 6 months. There can be daily fluctuation but the main point in this paper is to capture the main movements in which the trend is set over a period of months. We also have to set the minimum duration of a complete cycle. This is the time from the trough to the next trough. A problem arises if the data has the look of figure 1:

Figure 1: Copied from Bry & Boschan.



Should the swing a-b-c be regarded as a cycle or part of a larger expansion from a-d? A common rule used by the NBER is to set minimum duration of a complete cycle to at least 15 months, I set it to 16 months following Pagan and Sossounov (2003), since it gives a better result when fitting the bear and bull states to the price movements of the OMXS30.

As Pagan and Sossounov (2003) describes we can often see some sharp movements in stock prices, for example in 1987. Shortening the minimum phase could lead us to capture too many spurious cycles. Instead of changing the above rules an additional rule is instead set in place to disregard the minimum length of a phase (not cycle) if the stock price falls by 20% (Pagan and Sossounov 2003, Bry and Boschan 1971). It is important to note that the method has a drawback in real time lag, in my data the real lag is 5 months.

The code for this has been taken from NCER (National Centre for Econometric Research). As mentioned above the data used in the code from NCER is monthly prices on OMXS30 price index from 1986M2-2016M06.

## 2.4 EXPLANATORY VARIABLES

In choosing the explanatory variables I looked on previous research as for example, Pagan (2003), Song (2011), Keim and Stambaugh (1984), Chauvet Potter (2005), Nyberg (2013), Lunde and Timmermann (2004).

The data has been gathered from FRED (Federal Reserve Economic Data) and Datastream Reuters.

Nyberg (2013) showed in his paper that stock returns can have a predictive power when looking for bear and bull markets. Guidolin and Timmerman (2005) also showed that stock returns can have a high predictive ability on trying to predict regime switches in the stock market.

Chen (2009) showed in his paper that a multiple of variables have a significant effect on trying to predict bull and bear states. He continued to show that by just using one variable he could clearly beat the buy and hold strategy. The variables he used was the term spreads with different government bonds, like 10 years and 5 years. Narrow money growth showed some significant at longer lags, broad money gave good results for shorter lags. Inflation showed no effect but will still be used, since it can hold some expectation of future wages and costs. Industrial production growth also showed statistically significant results.

The purchasing manager index is supposed to reflect the expectations of companies hence their expected revenues which then will affect the stock prices (Guidolin and Timmerman 2005). The VIX index change does give information about the volatility, risk of the market.

Change in unemployment rates could have a predictive since consumption could go down given higher unemployment, which could hit corporation profits.

Additionally Chen (2009) found that the public debt, federal funds rates both had a significant effect on trying to predict bull and bear states. Rates has been used extensively in trying to predict recession with success, for example Erdogan, Bennett and Ozyildirim (2015) showed that using the yield curve had a high predictive power in trying to predict recessions.

For all the variables used in this paper unit root test were conducted to investigate whether the series are stationary, the result of the Augmented Dickey fuller, Phillips-Perron and Elliot-Rothenberg-stock DF-GLS tests are reported in table 4. It's also a good way to present the variables tested in table form.

Table 1  
Unit root tests

Variable	ADF	PP	DF-GLS
Nominal returns	-16.43	-16.41	-7.30
Market Liquidity Deviation	-2.36	-3.23	-1.88
Changes in Inflation rate	-12.93	-92.29	-0.16
Changes in dividend yield	-15.43	-15.25	-5.96
Changes in federal funds rates	-13.46	-136.88	-15.04
Changes In 10y government bond yield	-12.82	-12.95	-5.65
Changes In 5y government bond yield	-11.84	-11.86	-9.04
Changes in treasury bill rate	-21.66	-23.40	-1.00
Changes in price to earnings ratio	-18.42	-18.43	-6.74
Changes in VIX	-17.09	-30.37	-20.71
Changes in Purchasing manager index	-9.61	-17.17	-3.18
Changes in STIBOR 3M yield	-21.40	-22.36	-1.26
Growth rate of Public Debt	-2.47	-16.67	-2.05
Growth rate of narrow money (M0)	-2.18	-25.35	-2.18
Growth rate of broad money (M3)	-4.92	-38.20	-0.89
Growth rate of Industrial production	-23.62	-23.21	-0.83
Yield spread(10Y-3M)	-3.89	-4.36	-3.47
Term Spreads(5Y-3M)	-4.36	-5.01	-3.37
Term Spreads (10Y-3M)	-3.98	-4.48	-3.50

NOTE: ADF, PP, DF-GLS are Augmented Dickey-Fuller, Phillips-Perron and Elliott Rothenberg-Stock DF-GLS test statistics, respectively. The null hypothesis is always that the series has a unit root. Test critical for ADF and PP are -3.45 (1%), -2.87 (-5%) and -2.57 (10%). Test critical values for DF-GLS are -2.57 (1%), -1.94 (-5%) and -1.62 (10%).

The hypothesis of a unit root is rejected for all the variables at 10%. The only exception is the MLD which I will describe in more detail later. I will still use it in my analysis. The yield spread (the difference between the 10 year government bond and the 3-Month STIBOR). The term spreads are the difference between 10 years or 5 years government bonds with 3-Month Treasury bill rate. The federal funds rate is the marginal rate from 1986M01-1994M05 and the regular repo-rate from 1994M06-2016M06. Since Sweden changed from a fixed exchange rate to a floating exchange rate 1992, I have decided to only look at data from 1993. Around 1992 there are clear outliers which will distort my results, graphic motivation for this is presented in the appendix.

Market liquidity deviation (MLD) variable is based on a paper from Erdogan, Bennett and Ozyildirim (2015). They use the yield curve as many other papers, but what is interesting in their paper is that they use the variable they call a stock market liquidity deviation measure. They argue that given information shocks to the economy and the bond market, the equity market liquidity is being disrupted.

As agents become more uncertain about stock valuations, they may become more conservative in the depth of bids or offers they provide, raising price movements. This in turn lead to reduced volumes of securities

bought and sold, as informed agents become more reluctant to take positions, this can happen even if prices keep going up in bull markets but on thinner volume. Macro liquidity (ML) is measured as the log of equity market volume and macro depth (MD) is just the log of the value of securities. Both MD and ML are looked as relative to the log of GDP.

In this approach large deviations from the normal statistical relationship between the MD and ML signal an elevated likelihood of an economic recession, in this case I will use it for a signal of bear and bull markets. They used a linear regression model where the dependent variable was ML and explanatory variable was MD, which can be written as:

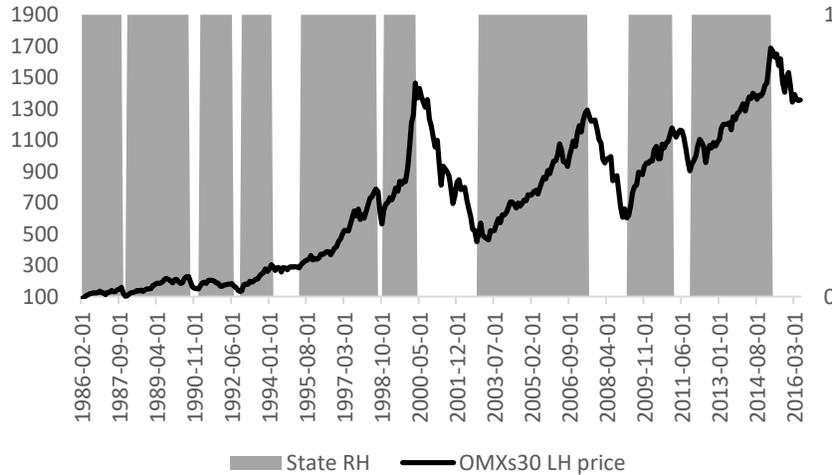
$$ML_t = \omega + \beta MD_t + \varepsilon_t \quad (10)$$

The residuals obtained from this regression are used as a measure of Market Liquidity deviation (MLD)

### 3 RESULTS

#### 3.1 RESULT OF BRY AND BOSCHAN ALGORITHM

Figure 2: Result following Bry and Boschan turning points.



Looking at Figure. 2 the grey area is the bull states while the white area are bear states. It seems that the algorithm with the rules I choose captures the regimes well, choosing different values for minimum phase and cycle, the result wasn't as good.

Table 2

Linear and Regime switching dynamics in stock returns

Peaks	Troughs	Bull duration	Bull Change%	Bear duration	Bear Change%
	(1986:06)				
1987:10	1987:12	17	81.94	2	-36.09
1990:08	1991:01	32	123.87	5	-34.31
1992:06	1992:10	17	23.09	4	-27.47
1994:02	1995:04	16	126.98	14	-6.71
1998:07	1998:10	39	176.96	3	-28.21
2000:03	2002:10	17	159.05	31	-69.03
2007:06	2009:02	56	185.03	20	-53.40
2011:01	2011:10	23	95.46	9	-23.29
2015:03	(2016:06)	41	86.84	15	-19.56

Notes: The first (second) column gives the peak (troughs) turning points of the OMXS30 index determined by the Bry and Boschan (1971) dating method. The sample period is 1986:02-2016:06. A bear market starts after the peak month and ends at the trough and vice versa with a bull market. Bull (bear) duration shows the time in months from the last trough (peak) to the next peak (trough). The percentage change in the OMXS30 index during the bear and bull is denoted by "Change%".

At the end of each new month, I reused Bry and Boschan algorithm to detect a possible turning point of the closing value of OMXS30. I did this to highlight the problems agents are faced with in real time. In doing so I found the same real time lag every time of 5 months.

Table3  
Mean and standard deviation of returns given regime. In %

Model	Linear	Regime switching
$\mu$	0.75	
$\mu_0$		-3.89
$\mu_1$		2.58
$\sigma$	6.42	6.42
$\sigma_0$		7.03
$\sigma_1$		5.13

Table 2 shows that bull markets tend to be longer than bear markets and the change in % is usually more in bull states. This follows Sossounov results showing that the durations of bear markets getting shorter given data past 1945. In 1987 we get a very short bear period of just 2 months. While the shortest bull period is of 16 months. Looking also at the bear market at 1994:02-1995:04, it is a period of 14 months but resulting in a decline of just 6.71%. Looking at the figure 1 it looks like the entire period is just flat. This a good clue of using just 2 states maybe aren't capturing all the dynamics of what is going on in the stock market. Song found in his paper evidence of a 4 state Markov regime switch model outperforming a Markov two state model (Song 2011).

Looking instead on table 3 we see the difference in regime in terms of mean and standard deviations. As expected the average mean is higher during bull markets and risk in the bear regime is higher. This give us more justification in trying to examine if the future bear and bull stock markets regimes are predictable. Given the result of table 1,2 and 3 we can clearly justify looking at a regime switching model.

If we break table 2 down in numbers we get table 4, again confirming that we have two different regimes.

Table4  
Bull and Bear breakdown.

Average duration of contractions = 11,44
Average duration of expansions = 29
Average amplitude of contractions = -44,54
Average amplitude of expansions = 74,95
Average cumulative movement of contractions = -327,43
Average cumulative movement of expansions = 1262,11
# of months in bull state = 262, 71.8%
# of months in bear state = 103, 28.2%

D=average duration, A=average amplitude, C=average cumulated movements

Number of peaks is given by:  $NTP = \sum_{t=1}^{T-1} (1 - s_{t+1})s_t$ . And average duration during expansion is therefore given by:  $\hat{D} = NTP^{-1} \sum_{t=1}^T s_t$ . Estimated average amplitude of expansions is given by:  $\hat{A} = NTP^{-1} \sum_{t=1}^T s_t \Delta \ln P_t$ .

To obtain the cumulated change over any expansion we just formulate a new variable  $Z_t = s_t Z_{t-1} + s_t \Delta \ln P_t$ ,  $Z_0 = 0$ . As long as  $S_t = 1$   $Z_t$  just contains the running sum of  $\Delta \ln P_t$ . When  $S_t = 0$  the sum is automatically reset to zero. That leads to the total of cumulated changes  $TC = \sum_{t=1}^T Z_t$  with the average being:  $\hat{C} = NTP^{-1} \sum_{t=1}^T Z_t$

Bear markets statistics are found in the same way by just replacing  $S_t$  with  $1-S_t$ .

## 3.2 RESULT OF PROBIT MODELS

Chen (2009) found that the term spread holds the strongest predictive power of all the variables he used. Nyberg (2013) found the same results. With this in mind we will start of by looking on all the different interest rate and spreads variables I have gathered. I have split the period from 1993M01-2016M06, in to two groups. The first sample is 1993:M01-2010M12, giving me a total of 216 observations to test the coefficients in. Then left for an out of sample result I have 66 observations, as mentioned in data the data description. The explaining variables are at first examined one by one in the static probit model. This is done to find the best lag and variables to use in a multivariate model, following Nyberg (2013). I will then look at an multivariate model dynamic model, to see if we get better fits and out of sample results.

### 3.2.1 In-sample Results

The empirical results for interest rates and spreads, including coefficient estimates, t-statistics, p-values and  $R^2$ , are reported in table 5. The interest rates looked at in table 5 are the first difference of the federal fund rate(ff), 5 year government bond(gb5), 10 year government bond(gb10), 3 month treasury bill rate(i) and 3 month stibor rate. The spreads in table 5 is the difference between 10 year government bond and 3 month treasury bill rate(termspread ts), 5 year government bond and 3 month treasury bill rate(termspread ts5) and the yield spread is given by the difference between the 10 year government bond and 3 month STIBOR(ys). I have looked at predictive ability of the lagged variables from 1:12, presenting lags with statistically significant results, the lags chosen to present is to show either rising or falling  $R^2$ . We see that the  $R^2$  is higher for the spreads over just the first difference of different interest rates. The federal fund rate has a high predictive power at lag 5. Looking at the spreads we find that the term spread (10Y-3M) has the strongest predictive power of all the variables given lag 11 and 12. Chen (2009) also found that term spreads at lag 12 gives the best predictive results in sample. Looking at lags beyond 12 for the term spread the  $R^2$  starts to drop off. The interest rates I will look at in my probit models are the term spread, yield spread and the first difference of the federal fund rate. This is because they have the highest predictive power  $R^2$ .

**Table 5**

In sample predictability test results for predicting stock markets

Standard probit model:  $\Pr(S_t = 1) = \Phi(\omega + \beta X_{t-k})$ 

Data for:1993:01-2010:12

	First difference of the federal fund rate					First difference of 5Y government bond					
	$\hat{\beta}$	(SE)	t-stat	p-value	$R^2$	$\hat{\beta}$	(SE)	t-stat	p-value	$R^2$	
k=1	-0.95	(0.48)	-1.98	0.048*	0.0202	-0.61	(0.33)	-1.83	0.068	0.0155	
k=2	-1.14	(0.50)	-2.30	0.022*	0.0294	-0.53	(0.33)	-1.61	0.106	0.0156	
k=3	-1.77	(0.55)	-3.22	0.001**	0.0542	-0.87	(0.34)	-2.58	0.010*	0.0337	
k=4	-2.39	(0.61)	-3.91	0.000***	0.0817	-0.96	(0.34)	-2.82	0.005**	0.0413	
k=5	-2.78	(0.65)	-4.26	0.000***	<b>0.1019</b>	-1.08	(0.35)	-3.13	0.002**	0.0510	
k=6	-2.44	(0.62)	-3.94	0.000***	0.0886	-1.25	(0.35)	-3.56	0.000***	0.0657	
k=7	-2.19	(0.59)	-3.69	0.000***	0.0811	-1.24	(0.35)	-3.54	0.000***	<b>0.0688</b>	
k=12	-1.33	(0.51)	-2.62	0.009**	0.0628	-0.41	(0.33)	-1.24	0.216	0.0406	
	First difference of 10Y government bond					First difference of 3M treasury bill rate					
	$\hat{\beta}$	(SE)	t-stat	p-value	$R^2$	$\hat{\beta}$	(SE)	t-stat	p-value	$R^2$	
k=1	-0.78	(0.35)	-2.20	0.028*	0.0211	-0.69	(0.41)	-1.66	0.098	0.0149	
k=2	-0.63	(0.35)	-1.78	0.076	0.0174	-0.70	(0.42)	-1.68	0.093	0.0181	
k=3	-1.01	(0.36)	-2.79	0.005**	0.0376	-1.29	(0.47)	-2.74	0.006**	0.0417	
k=4	-1.02	(0.36)	-2.81	0.005**	0.0408	-1.39	(0.48)	-2.91	0.004**	0.0492	
k=5	-1.06	(0.36)	-2.91	0.004**	0.0458	-2.22	(0.56)	-3.94	0.000***	0.0909	
k=6	-1.24	(0.37)	-3.34	0.001***	0.0598	-2.23	(0.56)	-3.94	0.000***	<b>0.0941</b>	
k=7	-1.18	(0.37)	-3.21	0.001**	<b>0.0599</b>	-1.72	(0.51)	-3.38	0.001**	0.0726	
k=12	-0.32	(0.35)	-0.91	0.361	0.0380	-1.10	(0.44)	-2.46	0.014*	0.0605	
	First difference of 3M STIBOR					Term Spread (10Y-3M)					
	$\hat{\beta}$	(SE)	t-stat	p-value	$R^2$	$\hat{\beta}$	(SE)	t-stat	p-value	$R^2$	
k=1	-0.69	(0.41)	-1.69	0.090	0.0168	k=1	0.35	(0.10)	3.650	0.000***	0.0567
k=2	-0.75	(0.41)	-1.81	0.071	0.0219	k=4	0.42	(0.10)	4.188	0.000***	0.0836
k=3	-1.65	(0.51)	-3.21	0.001**	0.0584	k=5	0.43	(0.10)	4.321	0.000***	0.0914
k=4	-2.06	(0.56)	-3.71	0.000***	0.0778	k=6	0.43	(0.10)	4.255	0.000***	0.0917
k=5	-2.18	(0.57)	-3.85	0.000***	0.0864	k=7	0.43	(0.10)	4.303	0.000***	0.0962
k=6	-2.38	(0.59)	-4.05	0.000***	<b>0.0987</b>	k=10	0.51	(0.10)	4.822	0.000***	0.1228
k=7	-1.85	(0.53)	-3.46	0.001**	0.0778	k=11	0.52	(0.11)	4.920	0.000***	<b>0.1298</b>
k=12	-1.08	(0.45)	-2.40	0.017*	0.0606	k=12	0.51	(0.11)	4.829	0.000***	0.1289
	Term Spread (5Y-3M)					Yield Spread (10Y-3M STIBOR)					
	$\hat{\beta}$	(SE)	t-stat	p-value	$R^2$	$\hat{\beta}$	(SE)	t-stat	p-value	$R^2$	
k=1	0.22	(0.10)	2.13	0.033*	0.0203	0.35	(0.09)	3.804	0.000***	0.0612	
k=2	0.24	(0.10)	2.32	0.020*	0.0265	0.37	(0.09)	4.010	0.000***	0.0708	
k=3	0.25	(0.10)	2.44	0.015*	0.0317	0.38	(0.09)	4.092	0.000***	0.0764	
k=8	0.35	(0.11)	3.29	0.000***	0.0653	0.40	(0.09)	4.282	0.000***	0.0970	
k=9	0.39	(0.10)	3.62	0.000***	0.0767	0.41	(0.09)	4.368	0.000***	0.1022	
k=10	0.43	(0.11)	3.91	0.000***	0.0880	0.42	(0.09)	4.409	0.000***	0.1060	
k=11	0.47	(0.11)	4.17	0.000***	0.0995	0.42	(0.10)	4.449	0.000***	<b>0.1102</b>	
k=12	0.47	(0.11)	4.20	0.000***	<b>0.1033</b>	0.41	(0.09)	4.430	0.000***	0.1078	

$R^2$  is a Pseudo R-squared measure. The one used in this table is Mcfaddens  $R^2$ .  $R^2 = 1 - (\ln \hat{L}(M_{full}) / \ln \hat{L}(M_{intercept}))$

k is the lagged time of the variable that I look at for example the term spread result for k=12, is just  $\Phi(\omega + \beta TS_{t-12})$ , so we look at one variable one lag at a time.

Bold entries indicate highest  $R^2$  for a given variable.

	FF	YS	TS
FF	1.0000		
YS	0.0717	1	
TS	0.0350	0.9705	1

Looking at a correlation matrix in table 6 we look at the three variables that will be considered in the multivariate probit model those are the term spread (TS) and the yield spread (YS) has the highest  $R^2$  and of the interest rates the federal fund rate (FF) has the highest  $R^2$ . In table 6 we see that using the TS and YS will give us problems with multicollinearity. But using both the term spread and the federal fund rate might not give rise to the same issues. I will look at multivariate models including both FF and TS.

Now we turn our attention to the remaining variables and the results for them are presented in table 7, I am showing the lags of the variable I deemed interesting in regard of  $R^2$ , to shorten the table again. All the variables has been tested with  $k =$  from 1 to 13, so again we just look at one variable one lag at a time.

**Table 7**

In sample predictability test results for predicting stock markets

Standard probit model:  $\Pr(S_t = 1) = \Phi(\omega + \beta X_{t-k})$ 

Data for:1993:01-2010:12

MLD = Market Liquidity Deviation					PMI = First difference of Purchasing manager index						
	$\hat{\beta}$	(SE)	t-stat	p-value	$R^2$		$\hat{\beta}$	(SE)	t-stat	p-value	$R^2$
k=1	4.10	(1.68)	2.44	0.015*	0.0247	k=1	5.95	(2.07)	2.88	0.004**	0.1585
k=3	7.23	(1.77)	4.08	0.000***	0.0716	k=2	5.29	(2.05)	2.58	0.010**	0.1607
k=9	10.96	(1.95)	5.61	0.000***	0.1559	k=3	7.07	(2.11)	3.34	0.000***	<b>0.1879</b>
k=12	12.52	(2.06)	6.09	0.000***	<b>0.1957</b>	k=4	4.28	(2.04)	2.10	0.036*	0.1696
PD = Growth rate of Public Debt					DYD = First difference of dividend yield						
	$\hat{\beta}$	(SE)	t-stat	p-value	$R^2$		$\hat{\beta}$	(SE)	t-stat	p-value	$R^2$
k=6	10.14	(4.47)	2.13	0.033*	0.0349	k=1	-1.75	(0.54)	-3.25	0.001**	<b>0.0471</b>
k=7	9.28	(4.73)	1.96	0.050*	0.0351	k=3	-1.19	(0.50)	-2.36	0.018*	0.0299
k=12	9.50	(4.84)	1.96	0.05	<b>0.0500</b>	k=5	-0.72	(0.48)	-1.51	0.132	0.0271
PED = First difference of Price to earnings ratio					VIX = First difference of volatility index						
	$\hat{\beta}$	(SE)	t-stat	p-value	$R^2$		$\hat{\beta}$	(SE)	t-stat	p-value	$R^2$
k=1	0.08	(0.04)	2.03	0.042*	<b>0.0208</b>	k=1	-0.69	(0.48)	-1.423	0.155	0.0108
k=2	0.07	(0.04)	1.72	0.086	0.0181	k=2	-0.80	(0.49)	-1.650	0.099	0.0161
k=3	0.05	(0.04)	1.23	0.22	0.0146	k=4	-0.78	(0.49)	-1.606	0.108	<b>0.0212</b>
rt = return of the stock market											
	$\hat{\beta}$	(SE)	t-stat	p-value	$R^2$						
k=1	7.39	(1.53)	4.84	0.000***	<b>0.1014</b>						
k=2	6.31	(1.49)	4.25	0.000***	0.0796						
k=3	4.91	(1.44)	3.41	0.000***	0.0548						
k=4	3.42	(1.41)	2.43	0.015*	0.0345						

Exd = First difference of exchange rate showed no statistical significance at any lag lengths from 1:12 and was left out of the table.

Inf d = First difference of inflation rate showed no statistical significance at any lag lengths from 1:12 and was left out of the table.

M0 = growth of Narrow money(nsa) showed no statistical significance at any lag lengths from 1:12 and was left out of the table.

M3 = growth of Broad Money showed no statistical significance at any lag lengths from 1:12 and was left out of the table.

Urd = First difference of unemployment rate showed no statistical significance at any lag lengths from 1:12 and was left out of the table.

Bold entries indicate highest  $R^2$  for a given variable.

Looking at Market liquidity deviation it is statistically significance and explains the state in which the market is in pretty good given a  $R^2$  of almost 20% for lag 12. Surprisingly the result give a higher explaining factor than the term spread, Erdogan 2015 never used the MLD for this but also found that MLD was statistically significant. I found even higher  $R^2$  at lag 13, but I decided against using it, at lag 14 the significance starts to drop off.

The purchasing manager index is only available from 1995, but it's statistically significant from k=1 to 3. After that it starts to drop off. It also shows good  $R^2$  results, making it interesting to use in my multivariable model.

The public debt variable only show significance at lags 6 and 7 with small values on  $R^2$ , the VIX shows none significance given  $p < 0.05$  at all lags. But it is significance at 10% at lag 2. It will be considered looking at the bigger model. Price to earnings ratio only show significance at lag 1. Looking at the similar ratio of dividend yield the highest  $R^2$  is at lag 1

again like the PED variable. Returns of the stock market is statistically significant and shows pretty good  $R^2$  measures. The result are not very different from results in previous paper, the only thing that stands out is the result for the MLD, this variable hasn't been used for trying to predict probabilities for stock market bull and bears, but maybe it should be considered more.

The signs of the coefficients are all expected. For example when PMI goes up, the value in  $\pi_t$  goes up, in return leading to higher probability of a bull market ( $s_t = 1$ ).

I will now turn my focus to using a multivariate probit model I will first look at the variables which indicated significance in the previous univariate probit models.

**Table 8**

In sample predictability test results for predicting stock markets  
Standard probit model:  $\Pr(S_t = 1) = \Phi(\omega + \beta X_{t-k})$ , intercept is not presented in table  
Data for:1993:01-2010:12

<i>Model 1</i>					<i>Model 2</i>			
Variable	$\hat{\beta}$	SE	t-stat	p-value	$\hat{\beta}$	SE	t-stat	p-value
MLD <sub>-12</sub>	18.60	3.81	4.882	0.000***	18.05	3.39	5.332	0.000***
PD <sub>-6</sub>	-2.29	8.19	-0.279	0.780				
TS <sub>-12</sub>	1.38	0.24	5.684	0.000***	1.36	0.23	5.951	0.000***
FF <sub>-5</sub>	-6.29	1.37	-4.588	0.000***	-6.05	1.22	-4.927	0.000***
DYD <sub>-1</sub>	0.00	1.20	0.001	0.999				
PED <sub>-1</sub>	-0.03	0.07	-0.441	0.659				
VIX <sub>-4</sub>	-1.15	0.75	-1.534	0.125				
RT <sub>-1</sub>	8.55	3.10	3.095	0.006**	7.82	2.16	3.619	0.000***
RT <sub>-2</sub>	5.38	2.15	2.158	0.013*	4.63	2.00	2.314	0.021*
RT <sub>-3</sub>	2.11	1.94	1.088	0.277				
AIC: 0.62641					AIC: 0.59997			
BIC: 0.80532					BIC: 0.69756			

Looking at model 1 in table 8 it includes the variables that showed to be statistically significant in table 5 and 7 using lags with highest predictive power. In model 1 we see that some variables are no longer statistically significant in the multivariate model, Public debt, dividend yield, price earnings ratio, VIX, stock market return of lag 3 all gets  $p > 0.1$ . The expected signs of the coefficients are again as expected, but not for price earnings ratio, though the result is insignificant. When the federal fund rate goes up, the probability of a bull state goes down. I have intentionally left purchasing manager index out of the models since I will lose observations given that it starts by 1995. I will instead try putting it in the final model to see if it adds value.

Dropping the insignificant variables from model 1 in table 8 we get to model 2. The coefficients do not change much, but the Standard errors falls compared to model one. Looking at a multivariate model it's a

smarter choice to look at a different model selection criteria than  $R^2$ . Instead I will be using Akaike information criterion (1937) and Schwarz Bayesian information criterion (1978). Comparing Akaike (AIC) and Schwarz (BIC) information criteria, we usually find that BIC favors the more parsimonious specification. In our case both AIC and BIC choose model 2 which is the more parsimonious model. I will continue with model 2, and we will now move beyond the normal static model, and start of by looking at the first extension.

Which is I will add  $\gamma s_{t-1} x_{t-h}$  to the model to see if the explanatory variables depend on the lagged value of the binary variable  $s_t$ .

**Table 9**

In sample predictability test results for predicting stock markets

Standard probit model:  $\Pr(S_t = 1) = \Phi(\omega + \beta X_{t-k} + \gamma s_{t-1} x_{t-h})$ , intercept is not presented in table

Data for:1993:01-2010:12

<i>Model 3</i>					<i>Model 4</i>				
Variable	$\hat{\beta}$	SE	t-stat	p-value	$\hat{\beta}$	SE	t-stat	p-value	
MLD <sub>-12</sub>	43.68	11.56	3.781	0.000***	42.41	10.59	4.004	0.000***	
TS <sub>-12</sub>	1.39	0.32	4.314	0.000***	1.40	0.24	5.799	0.000***	
FF <sub>-5</sub>	-6.96	2.11	-3.296	0.001***	-6.37	1.35	-4.713	0.000***	
RT <sub>-1</sub>	7.54	3.37	2.240	0.025*	9.49	2.46	3.853	0.000***	
RT <sub>-2</sub>	4.72	3.24	1.458	0.145	5.43	2.18	2.495	0.013*	
S1MLD <sub>-12</sub>	-28.19	11.39	-2.474	0.013*	-27.43	10.52	-2.607	0.013**	
S1TS <sub>-12</sub>	0.03	0.27	0.127	0.899					
S1FF <sub>-5</sub>	0.87	2.34	0.371	0.711					
S1RT <sub>-1</sub>	4.01	4.86	0.827	0.408					
S1RT <sub>-2</sub>	0.88	4.81	0.183	0.855					
AIC: 0.60392					AIC: 0.56898				
BIC: 0.78284					BIC: 0.68284				

In using eq. (4) we get results shown in table 9 in model 3. Comparing AIC and BIC of model 3 with model 2 we can see that model 3 is worse than model 2. Out of the 4 new variables generated there is only one that is statistical significant and that is the market liquidity deviation variable.

This leads me to look at model 4 again in table 9, clearing all the other variables multiplied with the dependent variable  $s_1$  except for MLD. Now the model looks much better and both AIC and BIC choose model 4 over model 2. All the coefficients are statistically significant and show the expected sign. Model 4 shows that the MLD has a smaller impact during bull markets than during bear markets.

Comparing model 2 with model 4 both AIC and BIC indicate that model 4 is superior so there seems to be some asymmetry in market liquidity deviations effect on the conditional probability.

Table 10 shows results of using eq. (3) by adding  $s_{t-1}$  in to model 2.

**Table 10**

In sample predictability test results for predicting stock markets

Standard probit model:  $\Pr(S_t = 1) = \Phi(\omega + \beta X_{t-k} + \delta s_{t-k})$ , intercept is not presented in table

Data for:1993:01-2010:12

Model 5					Model 6				
Variable	$\hat{\beta}$	SE	t-stat	p-value	$\hat{\beta}$	SE	t-stat	p-value	
MLD <sub>-12</sub>	12.28	5.38	2.284	0.022*	15.52	3.54	4.380	0.000***	
TS <sub>-12</sub>	0.779	0.34	2.264	0.024*	1.23	0.24	5.101	0.000***	
FF <sub>-5</sub>	-5.57	2.21	-2.518	0.012*	-5.55	1.28	-4.33	0.000***	
RT <sub>-1</sub>	-5.63	3.70	-1.521	0.128	6.25	2.24	2.793	0.005*	
RT <sub>-2</sub>	-1.53	3.34	-0.458	0.657	4.06	2.10	1.936	0.053	
S <sub>-1</sub>	3.68	0.64	5.781	0.000***					
S <sub>-5</sub>					0.82	0.30	2.735	0.002**	
<b>AIC: 0.28847</b>					AIC: 0.57330				
<b>BIC: 0.40233</b>					BIC: 0.68716				

As expected both AIC and BIC choose the model with  $S_{t-1}$ , but lagging the state variable with just one lag is hard to use in practice, because of the real time lag at 5. That is the real values of  $S_{t-1}$ ,  $S_{t-2}$ ,  $S_{t-3}$  and  $S_{t-4}$  aren't revealed in the Bry and Boschan algorithm until month 5. So the market could already have been in switched from a bear state to a bull state and your  $S_{t-1}$  would still be at a bear state. So I also looked at lagged state variable at 5, giving me model 6. Looking at BIC and AIC model 5 is still preferred but model 6 is the one that could actually be used in practice. Removing  $rt_{-2}$  in model 6 gives a BIC (AIC) value of 0.67972 (0.58213). So here BIC and AIC gives different results, I will choose to remove  $rt_{-2}$  and looking at the more parsimonious model.

I will keep model 5 as a comparing illustration and because Nyberg (2013) showed that at higher forecast horizons with a rolling windows of  $s_{t-1}$  is a model that can actually be used in practice. Adding  $S1MLD_{-12}$  to both model 5 and 6 we get better results of BIC and AIC, the values for model 6 BIC (AIC) are 0.65542 (0.54156). Adding purchasing manager index I got the result that PMI wasn't statistically significant in model 5 and model 6 at 5% level. So the two main models will be model 5 and 6 with  $S1MLD_{-12}$  variable added to both of them, I will call the two models, model 7 and 8.

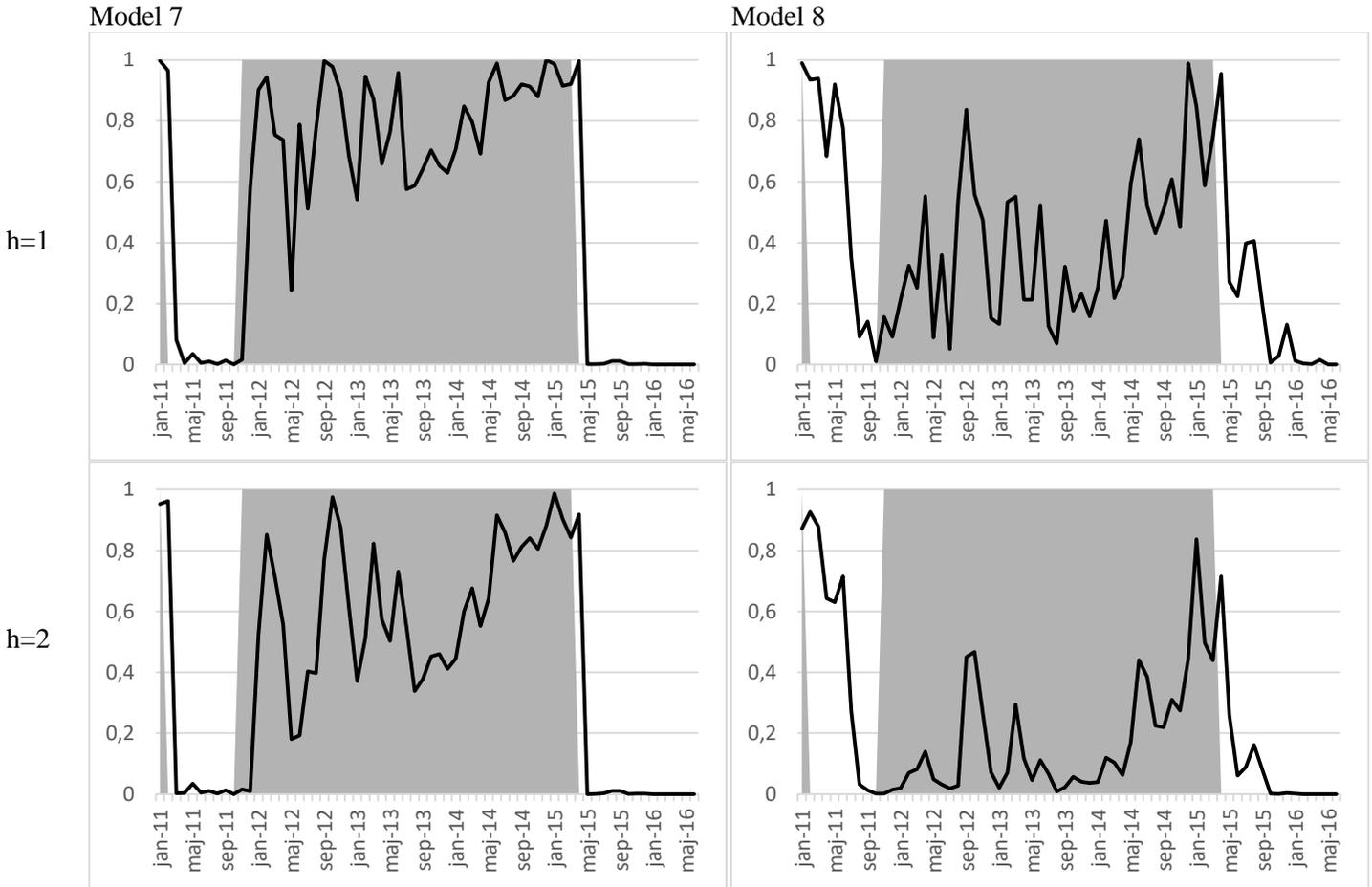
### 3.2.2 Out of sample results

Again the out of sample period is 2011M01:2016M06. We will start of by looking at horizon 1 for model 7 and 8. The two models could be written as:

$$\begin{aligned}
 \text{Model 7} &= p_t = \Phi(\omega + \beta_1 MLD_{-12} + \beta_2 TS_{-12} + \beta_3 FF_{-5} + \gamma s_{t-1} + \delta s1MLD_{-12}) \\
 \text{Model 8} &= p_t = \Phi(\omega + \beta_1 MLD_{-12} + \beta_2 TS_{-12} + \beta_3 FF_{-5} + \beta_4 rt_{-1} + \gamma s_{t-5} \\
 &\quad + \delta s1MLD_{-12})
 \end{aligned}$$

From figure 3 we can see that both models seem to give a better result for  $h=1$ . Which is the most interesting horizon for agents, since they are more concerned about what happen next.

Figure 3: Result from model 7 and model 8 given  $h=1$  and  $h=2$ .



Probabilities for a bull market are given by the black line, while the grey area is periods in which OMXS30 is in a bull market.

So I will focus on horizon one from here on out, which is the most interesting horizon anyway given we are interested in regime switches. Model 7 seems to follow the true values by just one month, this is to be expected since the result resemble a linear AR(1) regression model. Model 8 is slower to predict the true values.

I will now look at how well the models predict the true model given a threshold value. The threshold will be set to 0.3, following Chen (2009) seems reasonable given that our data has 28.2% bear regimes. The result is presented in table 11.

Table 11 clearly favors model 7 over model 8. Model 8 don't show great results for out of sample results.

**Table 11**

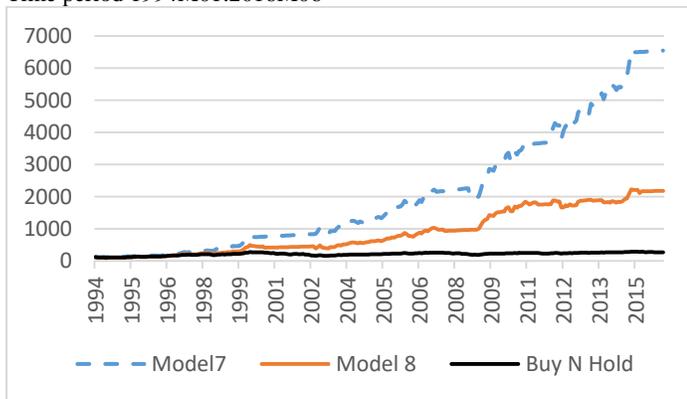
Comparison of models given predicted value.

	Model 7	Model 8
Predicted Bull months	42	33
Predicted Bear months	24	33
Correct # of bull in %	97.62%	57.14%
Correct # of bear in %	91.67%	62.50%
Overall in %	93.94%	59.09%

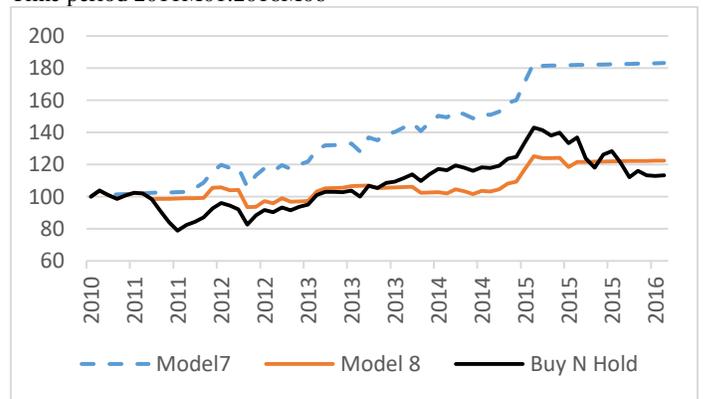
Model 7 predicts right results in overall of 93.94% this is a very high number, but again it just lags the true values with one month. When the economy is in bull state model 8 gives the correct estimation 57% of the time. The result for bear markets are a little better at 62.5%.

Finally we will investigate if trying to predict bull markets adds any economic value to market participants, in timing market fluctuations. I will look if by using the 0.3 threshold on model 7 and 8 if the switching strategy is more profitable than the buy and hold strategy (no transaction costs included). I will look at two time periods, one from 1994M01:2016M06, that is the entire data period and the other is just the out of sample period.

Figure 4: Economic value of model 7 and model 8  
Time period 1994M01:2016M06



Time period 2011M01:2016M06



In the full timespan the Buy-N-Hold strategy is beaten quite significantly using both models, while model 8 only slightly beat the Buy-N-Hold in an out of sample period. This is done to exemplify the usefulness of predicting a bear market. We can see that by just avoiding bear markets model 8 actually beats the Buy-N-Hold strategy. This is in line with what Chen (2009), Nyberg (2013), Erdogan, Bennett and Ozyildirim (2015) and Seidl (2012) found.

## 4 CONCLUSION

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This paper investigate whether a simple static and dynamic probit model are useful in predicting Swedish bull and bear in the stock market. To do this I first found the turning points, peaks and troughs of OMXS30, using past information available to investors in real time. Using a mix of variables in a single a multivariate static and dynamic probit model, I found predictive power on a series of variables and even though the results leave a lot of room to improvement, there is some usefulness of the model implemented. I found that the best leading indicators was the term spread, interest rates and market liquidity deviation. The best results was found using all the variables together in a dynamic model.

By doing this simple strategy I found that one could improve returns over the simple buy and hold strategy of an index. I would have wished for a bigger sample of data and especially for an out of sample investigation.

The dynamic model as previous research found yield superior results compared to just the static model. Song (2011) found a 4 four regime Marko switching model that improved results over just a 2 regime model. Some further research has been done in looking at more extensions of the model like the autoregressive dynamic probit model Nyberg ( 2013) found evidence of improvement using the autoregressive probit model. Candelon, Piplack and Straetmans found evidence of synchronization between markets in the case of East Asia, and they found that synchronization is increasing. One should therefore maybe also look at different macro variables from different countries. This same procedure could be done for the Scandinavian countries and European countries in trying to capture more dynamics of the market.

The evidence is for me very interesting and the model could be looked at for many different markets not just stock markets. Combining this with some other predicting models should further improve results. For example combining it with a simple book to market ratio measure. The chase for a model that could outperform the stock market continues.

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# APPENDIX

Different interest rate and interest rate spreads.

