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Predicting Market Crashes: An Examination of the Performance of Macroeconomic Indicators and Technical Analysis

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ABSTRACT

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The purpose of this study is to examine macroeconomic indicators' and technical analysis' ability to signal market crashes. Indicators examined were Yield Spread, The Purchasing Managers Index and the Consumer Confidence Index. Technical Analysis indicators were moving average, Moving Average Convergence-Divergence and Relative Strength Index. We studied if commonly used macroeconomic indicators can be used as a warning system for a stock market crashes as well. The hypothesis is that the signals of recession can be used as signals of stock market crash and that way a basis for a hedging strategy.

The data is collected from the U.S. markets from the years 1983-2010. Empirical studies show that macroeconomic indicators have been able to explain the future GDP development in the U.S. in research period and they were statistically significant. A hedging strategy that combined the signals of yield spread and Consumer Confidence Index gave most useful results as a basis of a hedging strategy in selected time period. It was able to outperform buy-and-hold strategy as well as all of the technical indicator based hedging strategies.

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Tämän tutkielman tarkoituksena on tutkia makrotaloudellisten indikaattoreiden ja teknisen analyysin kykyä signaloida markkinoiden romahduksia. Tutkimamme indikaattorit ovat korkoero, ostopäällikkö indeksi ja kuluttajien luottamus indeksi. Teknisen analyysin indikaattoreita ovat liukuva keskiarvo, MACD -indikaattori sekä suhteellinen vahvuus indeksi. Tutkimme pystytäänkö yleisesti käytettyjä makrotaloudellisia indikaattoreita käyttämään signaloimaan myös osakemarkkinoiden romahdusta. Hypoteesina on että taantuman signaaleja voidaan hyödyntää merkkinä osakemarkkinoiden romahduksesta ja näin rakentaa indikaattoreiden pohjalta myyntioptioilla toteutettu suojaus strategia.

Käytetty data on kerätty USA:n markkinoilta vuosilta 1983-2010. Empiiriset tutkimukset osoittavat että makrotaloudelliset indikaattorit ovat pystyneet selittämään tulevaisuuden BKT:n vaihteluita USA:ssa tutkimusaikana ja ne ovat olleet tilastollisesti merkitseviä. Suojaus strategia, joka yhdistää korkoeron ja kuluttajien luottamus indeksin signaalit, tuotti käytännöllisimmät tulokset tutkimusperiodilla. Tämä strategia pystyi tuottamaan paremmat tulokset kuin tekninen analyysi tai osta ja pidä -strategia.

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1 INTRODUCTION

Economists and market participants have certain models and indicators about the state of the economy and possible direction of its development. With these macroeconomic indicators they are trying to anticipate the turning points of the economic cycle. There are several indicators and methods which try to predict economy's development and cycle's turning points. In this study we introduce a few commonly followed and frequently published macroeconomic indicators, which are commonly used to indicate the direction of the economy and possible recession. These indicators have been in the center of economic studies and financial press in recent years. Macroeconomic indicators that we use are 1. Spread between 10 year and 3 month interest rate (Yield Spread). 2. The Purchaser Managers Index (PMI) and 3. The Consumer Confidence Index (CCI). We also introduce three different technical indicators, which are commonly used to predict stock market trends. These technical indicators are: Moving Average (MA), Moving Average Convergence-Divergence (MACD) and Relative Strength Index (RSI).

The purpose of this study is to find out if commonly used macroeconomic indicators, used to signal and predict future GDP changes, can be used as a warning system for stock market crashes. The hypothesis is that the signals of a recession can be used as signals of stock market crash and this way as a basis for a hedging strategy. We also investigate and compare the performance of another predicting method which is based on historical stock market data, and were the changes in the future stock returns are predicted from the historical changes. This is commonly called as technical analysis. Technical analysis has been a subject for financial press articles, where portfolio managers are predicting trends in the stock market basing these predictions with technical analyze indicators. The research problems we examine in this paper can be expressed as following questions:

1. Has macroeconomic indicators been able to explain the future development in U.S. GDP and has the indicators explanatory power been statistically significant?
2. Has the macroeconomic indicators signaled the recession in time, so that an equity investor would be able to hedge ones portfolio and used the macroeconomic indicators as a warning system?
3. Has a hedging strategy build on the base of the signals of a recession been effective in selected time period and has it been able to beat strategies which are based on commonly used technical analysis indicators over the selected time period?
4. Has a hedging strategy build on the base of the signals of a recession been able to outperform a buy-and-hold strategy over the selected time period?

Predicting stock market crashes from macroeconomic variables derives from the fact that stock market is an indicator of real economy and when we expect that the economic cycle is about to take a turn for a worse, the stock market reacts to this fear. Chen (1991) studied this relationship and concluded that: "*The collective evidence presents a unifying story that relates the ability of the state variables to forecast the market premium to their ability to forecast recent and future growth of the economy."* Chen's (1991) conclusion brings us to our research question 1 of how well the indicators we examine have been able to explain the future growth in GDP in last 26 years.

Empirical research and test how well the indicators would have worked is done by back testing. We use market data gathered from the U.S. markets form years 1983-2010. Data used to perform the econometric tests is quarterly data, since GDP numbers are announced quarterly. The data used to evaluate the relationship to the stock market is monthly data. This relationship is studied from the years 1999-2010. The performance evaluation is done by comparing our macroeconomic indicators based strategies to passive buy-and-hold strategy and strategies which are based on technical analysis indicators. We compare these different strategies by using common performance evaluation measures like profit, volatility and reward-to-variability ratio. We are going to investigate empirically how this kind of market analysis would have worked in last decade. The indicators we use in our examination are based on macroeconomics, hence hedging strategies based on Yield Spread, PMI and CCI are fundamentally based on macroeconomic data.

The results of this study show that macroeconomic indicators have been able to explain the future GDP changes in the U.S. and they have been statistically significant. Results also show that Yield Spread has been reacting to the threat of a recession before the S&P 500 index in selected investing period, but the S&P 500 index has been leading Purchaser Managers Index and Consumer Confidence Index. When comparing the indicators as a basis for hedging strategy, the results show that the most useful strategy for an equity investor's point of view in the last decade would have been a combination of the yield spread and Consumer Confidence Index. This kind of strategy was able to beat technical indicators as well as buy-and-hold strategy in terms of profit and in reward-to-variability ratio.

In section 1 we introduce previous academic literature related to prediction of recession, stock market returns and indicators we use. In section 2 we explain the theoretical background of the indicators and methods how to interpret them. Section three introduces the methodology of empirical research. Section 4 is devoted to the results and findings of the study. Section 5 concludes.

1.1 Motivation

Many previous academic studies have examined the prediction power of macroeconomic variables and proven the relationship between e.g. different yield spreads and GDP development. We wanted to examine that relationship with selected macroeconomic variables and GDP changes existed over the last 26 years and that relationship has been statistically significant. Furthermore we wanted to examine the relationship between selected macroeconomic indicators and the stock market. Stock market is also an indicator for real economy and for investor's point of view it is important to know which of these indicators has been indicating the recession first. Predicting of recessions from the financial and macroeconomic indicators, such as yield spread has been studied for example by Harvey (1989 and 1991), Estrella and Mishkin (1998) and Duarte et.al. (2005). Predicting the likelihood of a recession is important so that businesses can plan their strategies and budgets should the downturn occur. Policymakers have also use for these kind of predictions and analyses of the likelihood of a recession, so they can make the decisions and plans how to ease out the economy if the downturn occurs.

However, in this study we concentrate to study the usefulness of the indicators' signals of a recession in equity investors' point of view. Macroeconomic indicators ability to indicate the economic turn and possible recession has been the interest of the academic literature for numerous times, but the ability to warn about the stock market crash has not been as widely investigated. The relationship between stock market returns and macroeconomic indicators was studied for example by Chen (1991) and Campbell (1987) who studied the term spreads ability to predict market returns. However, these previous studies did not address to the question if macroeconomic indicators would provide effective warning signals for an equity investor in terms of possible stock market crash and if these indicators could be used as a base for a hedging strategy. This is a question that many investors would have wanted to know an answer to for example in December of 2007. PMI and CCI are published monthly and their levels and development widely attract media's and investors attention. This is why we wanted to evaluate should an equity investor in fact pay attention to these macroeconomic indicators and would they have been useful in terms of avoiding recession related stock market crashes in selected time period.

1.2 Related Literature

Estrella and Mishkin (1998) studied the usefulness of financial variables in out-of-sample predictions regarding U.S. recession and whether or not the U.S. economy will be in a recession anywhere between 1 and 8 quarters in the future. The financial variables they used were interest rates, interest rate spreads, stock price indexes, and monetary aggregates. Estrella and Mishkin (1998) examined these indicators by themselves and in some plausible combinations. The results they got were compared with different, more traditional, leading macroeconomic indicators. Estrella and Mishkin (1998) concluded that yield curve spread and stock prices can play a useful role in the prediction. These simple financial indicators may be observed individually over their respective primary horizons or they could be combined to produce a simple but reliable model. They also concluded that this model would have provided some warning of the recession of 1990 – 1991 over four quarters ahead, even though that recession in the U.S. had some unusual events such as the gulf war.

Harvey (1989) studied yield curve measures and stock market variables and the relevance of the information that these indicators gave to the prediction of the GNP growth. Harvey (1989) concluded that the yield spread was able to explain over 30 % of the variation in the GNP growth over the 1953-1989 period, when the stock market variables were able to explain only about 5 % of the variation in GNP growth in the same period. Harvey (1989) used a simple linear model to make his analysis and forecast. Harvey (1991) studied a similar subject again using the same forecasting model but this time he studied the term structure's ability to predict worlds GNP growth. He compared different forecasting models to the linear model based on term structure and concluded that term structure model was able to give the most accurate predictions. Harvey (1991) concluded that term structure was able to provide early warning signals of recession in 1973 and 1980.

Duarte et.al. (2005) studied the predicting of total growth and probability of recession in the Euro area by using the yield spread. Their data sample was from the years 1970-2000. They used both linear and non-linear models when contracting their study. Their conclusion was that term spread of the Euro area is in fact a useful indicator of future growth and as well the future recessions in the Euro area. Both linear and nonlinear threshold indicator models were able to predict reasonably well the output growth for four quarters ahead. Duarte et.al. (2005) studied the power of predicting the recession in Europe, by using a probit model using yield curves from Euro area and U.S. Their results were supported by both in-sample and out-of-sample probit predictions. In both, the model was able to predict major recessions in the Euro area at least three quarters ahead.

Also Moneta (2005) studied yield spread's predictive ability in the Euro area. Moneta (2005) tested ten different variations of the yield spreads, for different segments of the yield curve. The study was conducted by using a probit approach. He concluded that the ten-year government bond rate and the three-month interbank rate were able to outperform all other spreads in predicting recessions in the euro area. The forecast accuracy was explored also in out-of-sample forecasting. The yield spread appeared to contain information beyond that already available in the history of output. Yield spread was also able to outperform other competitor indicators.

Chauvet and Potter (2002) studied the yield curve's predictive power in the presence of structural brakes. They found extremely different results in predictions between models that assumed: no break, fix the brake at particular date or estimate break endogenously. Chauvet and Potter (2002) developed a Gibbs sampling algorithm for estimating the effects of structural breaks on recession probabilities from probit models. This algorithm was used to address the probability of a recession in December 2001. They founded considerable uncertainty over the value of this probability. This was due to uncertainty over the correct breakpoint. The authors viewed this uncertainty as reflecting the fact that each business cycle is different.

While many studies examine the yield curve's ability to predict GDP and the turn in the economic cycle, not as many have investigated the yield curve's role in predicting the stock market returns. Naturally, the anticipated direction in the overall economy and economic conditions affect the investors' sentiment, but can this be implemented in a way that it is possible to predict stock market returns from the yield curve? Campbell (1987) examined the effect of term structure to the stock returns and found out that risk premium on stocks appeared to move together with 20-year Treasury bonds, while the premium on Treasury bills seemed to move independently. He also found statistically significant evidence that in fact there are predictable movements in excess returns on bills, bonds and stocks and these movements are partially captured by a different term structure variables. Moreover Campbell (1987) found out that the evidence for bill and stock returns were very strong and predictable movement in bond and stock returns were highly correlated. Chen (1991) studied the stock market premium prediction from the macroeconomic indicators, such as lagged production growth rate, the default premium, term premium, short-term interest rate and the market dividend-price ratio. He came to conclusion that the market excess return is negatively correlated with recent economic growth and positively correlated with expected future economic growth. He also states that the result of his study offers tools to use forecasts on the macro economy to forecast market excess returns.

Dotsey (1998) studied the forecasting ability of the term spread. He used data from 1956-1997 and made also a graphical analyses of the signals, which term spread had provide. He concluded that term spread was able to give true signals about recession about 83 % of the time. Dotsey (1998) used method that the signal was true if the spread turned negative concurrently or within one-to-four quarters of the signal. In his study he made in-sample and out-of-sample predictions using regression models. He concluded that term spread has been a useful leading indicator of economic activity. However he also mentions that over more recent periods the spread has not been as informative as it had been in the past.

Koenig (2002) examined the Purchasing Managers Index’s ability to predict the turning points in the economical cycle. According to Koenig’s (2002) study, the index is important and deserves the attention it has received as an indicator of changes in total economic activity. When considering this index alone its levels are what matters. According to Koenig’s (2002) study and regression model, the readings above 40 have signaled an expanding in the whole economy. When the index is considered in conjunction with recent jobs, sales and factory output data, one should look the index change and its direction. Koenig (2002) writes that a rising PMI signals that GDP growth is likely to be stronger than earlier estimates would suggest.

Jansen and Nahuis (2003) studied the short-run relationship between stock markets and consumer confidence in European countries. Their research period was 1986-2001. Their main conclusion was that the stock market development was able to forecast the changes in Consumer Confidence (in the short-run), but not vice versa. Their examination suggested that mentioned relationship is driven by expectations about economy-wide conditions more than personal finance issues. Another study of the Consumer Confidence Index and its relationship with the stock market was conducted by Fisher and Statman (2003). They found that S&P 500 affects the consumer confidence. When the S&P 500 returns rose, the Consumer Confidence Index increased as well. They found statistically significant relationship between S&P 500 index returns and consumer confidence. They also investigated other indices to determine whether or not consumer confidence can predict stock returns. Fisher and Statman (2003) found that consumer confidence was able to predict some stock returns, when predicting Nasdag and small cap stock returns. They found negative and statistically significant relationship between level of the expectations component of the Conference Board confidence in one month in Nasdag and small cap stocks in the following month. However, they did not find that the same relationship to be statistically significant when considering the S&P 500 index.

Batchelor and Dua (1998) investigated if Consumer Confidence Index would be able to improve macroeconomic forecasts. They examined how well Consumer Confidence Index was able to predict changes in the economy and compared it to forecasts made by professional economists. They also compared consumer confidence based forecast to consensus forecast made by Blue Chip Economic Indicators service. Their concluding comment was that use of the consumer confidence would have helped to predict the 1990 recession, but other times the attention to consumer confidence would have been misleading.

Technical analysis has faced contradictory results in academic literature. Many researches (see e.g. Fama (1965), Neftci (1991)) have concluded that technical analysis is not able to predict future movements in the stock market and that simple buy-and-hold strategy outperforms trading rules. On the other hand there are studies which conclude that use of the trading rules has been effective and they have been able to beat the buy-and-hold strategy. Mills (1997) studied the trading rules using the data from London Stock Exchange FT30 index for the period of 1935-1994. He examined the strategy's statistical significance via AR-ARCH models and by bootstrap techniques. He found that the rules actually worked for the most of the sample period, at least up to the 1980's. However these findings were also contradictory, since after 1980's the buy-and-hold strategy dominated the trading rule strategy. Mills (1997) tested the moving average trading rule and his examination was re-exanimate by Chong and Ng (2008). They examined the same data set, but divided the data into three samples and studied the RSI and MACD trading rules. They concluded that RSI and MACD trading rules were able to out-perform the buy-and-hold strategy and that this conclusion was robust to their choice of the sample period. The returns for the trading rules were statistically significant at the 5 % level.

2 THEORETICAL BACKGROUND

2.1 Relationship between Recessions and Stock Market Crashes

Of course a vital thing for having use for the prediction of a recession in the equity investors' point of view relates to the stock markets. Does total output effect the stock market and how much? Valuation of a stock is the present value of all the cash flows it generates in the future. This way growth of total output naturally effects the valuation and the expected returns that an investor will expect from his or hers investment. One could also assume that if recession is expected, the average risk aversion of the investors will grow and optimal portfolios will contain more riskless assets, hence stocks are not that attractive when recession is expected and investors are selling their more risky investments. Investors are putting their savings into less riskier assets like bonds, savings accounts or maybe even under the mattress.

We could also assume that dividends and earnings per share reduce in a recession. There are differences among industries and some are more sensitive to cyclical movements, but we can assume that in whole the stock market is influenced negatively by recession. Let's consider the basic valuation model of an asset or investment, which is shown in equation 1. It is based on the expected future cash flows and of course also the rate of return which those future cash flows are discounted with. If markets are expecting a recession the expected growth rate on cash flows and dividends is going to reduce. The possibility of default is also larger in recession for most companies, so discount rate is going to be larger in recession. Both of these have an effect in valuation model, and both of them are reducing the Net present value of the stock, thus current price.

$$\mathrm{P_0} = \frac{\sum_{\mathrm{t}}^{\infty} \mathrm{CF}}{\mathrm{R_t}} \tag{1}$$

In equation 1 $\mathrm{P_0}$ is the current price of the stock, $\sum_{\mathrm{t}}^{\infty} \mathrm{CF}$ is sum of the expected cash flows and $\mathrm{R_t}$ is the discount rate.

Fama (1990) studied how well does the total activity explains the annual returns in stock markets. His conclusion was that total activity explains 59 % of the variance of annual returns on the value-weighted portfolio of NYSE. His test suggest that a large fraction of the variation of stock returns can be explained by time-varying expected returns and forecast of total activity. Another study considering changes in macro economy and investment opportunities was done by Chen (1991). He came to conclusion that the market excess return is negatively correlated with recent economic growth and positively correlated with expected future economic growth.

Chen (1991) explains the theoretical background for the relationship between the macroeconomic conditions and asset prices. As Chen (1991) points out, asset pricing models developed from example by Cox, Ingersoll, and Ross (1985) among others, are modeling the relationship between macroeconomic conditions and asset prices. These asset pricing models describe expected returns as functions of variables that describe the macro economy; hence the expected return (equilibrium price for the asset) derives from the macroeconomic conditions. Chen (1991) also argues that since financial securities are claims against future output, a change in expected economic health will generally affect the expected returns of the securities. The described relation of the macroeconomic conditions and stock market returns derive certain hypothesis, which was examined empirically by Chen (1991). First the risk aversion implicit in the pricing of securities and the expected market premium are negatively correlated with the current health of the economy. Second, as mentioned above, financial securities are claims against future outputs, a variable which measures the expectations of the future productivity of capital should be positively correlated with the expected rate of return and the market premium. Third, the expected market premium is positively correlated to a measure of the conditional uncertainty of the production technology.

As mentioned above Chen (1991) studied the mentioned hypothesis empirically. He concluded that the default spread, term spread, the one-month T-bill rate, the lagged industrial production growth rate, and the dividend-price ratio are important determinants of future stock market returns. Chen (1991) examined the ability of variables mentioned above, to predict future market returns, in terms of their correlation with macroeconomic changes. Chen (1991) also found that mentioned variables were related to the recent and future GNP growth. Chen (1991) mentioned in his conclusion that the evidence of his research showed that ability of variables to forecast the market premium relates to their ability to forecast recent and future growth in the economy.

Taking a simple numerical analysis of last three U.S. recessions and stock market development, presented in table 1, we can see that the annualized quarterly total returns of the S&P 500 index faced a major downturn in some point of each recession. In 1990 the recession was started, according to the National Biro of Economic Research (NBER), in July, which is first month of the third quarter. We can see from table one, that the totalized total annual returns from that quarter (in quarter 3 in 1990), was -50.83 % (total return from the Q3/1990 was -16.3%). In each of the last three U.S. recessions, the S&P 500 returns have taken a major hit around the start of the recession. The index has gone downhill before the recession has started and also during the recession.

When considering the usefulness to predict the change of direction in the economy, especially in the investors’ point of view, we can say that recent history and academic literature gives us examples that stock markets are affected from the total growth and, naturally, expectations of the total growth.

Table 1. Annualized Quarterly returns of the S&P 500 total return index

Quarter	Annualized total return
Q2 1990	39.74%
Q3 1990	-50.83%
Q1 2001	-46.22%
Q2 2001	40.91%
Q3 2001	-51.33%
Q4 2007	-37.42%
Q1 2008	-17.25%
Q2 2008	-9.15%
Q3 2008	-8.30%
Q4 2008	-74.24%

Table 1 provides the annualized total returns of S&P 500 index from quarters around the time of last three U.S. recessions announced by NBER. Returns were annualized from logarithmic quarterly returns.

2.2 Macroeconomic Indicators

2.2.1 Yield Spread

The yield spread is the difference between a long-term interest rate (e.g. a 10-year government bond) and a short-term interest rate (e.g. 3-month Treasury bill). There are several studies that proofs that the yield curve contains information about the future economic activity and thus information about the upcoming recession. See e.g. Harvey (1988, 1989), Duarte et.al. (2005). Moneta (2005) explains the relationship between the yield spread and the total economic growth. Yield Spread reflects the expectations that financial markets participants have of the future economic activity and growth. A steepening of the yield curve (a positive spread) is associated with an increase in total economic activity and a flattening of the yield curve (a negative spread) is associated with a decline in total activity. There are three main explanations why the slope of the yield curve contains relevant information about the future economic activity.

According to Moneta (2005), the expectations hypothesis of the term structure of interest rates states that the long-term rates reflect the expected path of the short-term interest rates as presented in equation 2.

$$(1 + r_2)^2 = ((1 + r_1) \times (1 + E(r_1)) \qquad (2)$$

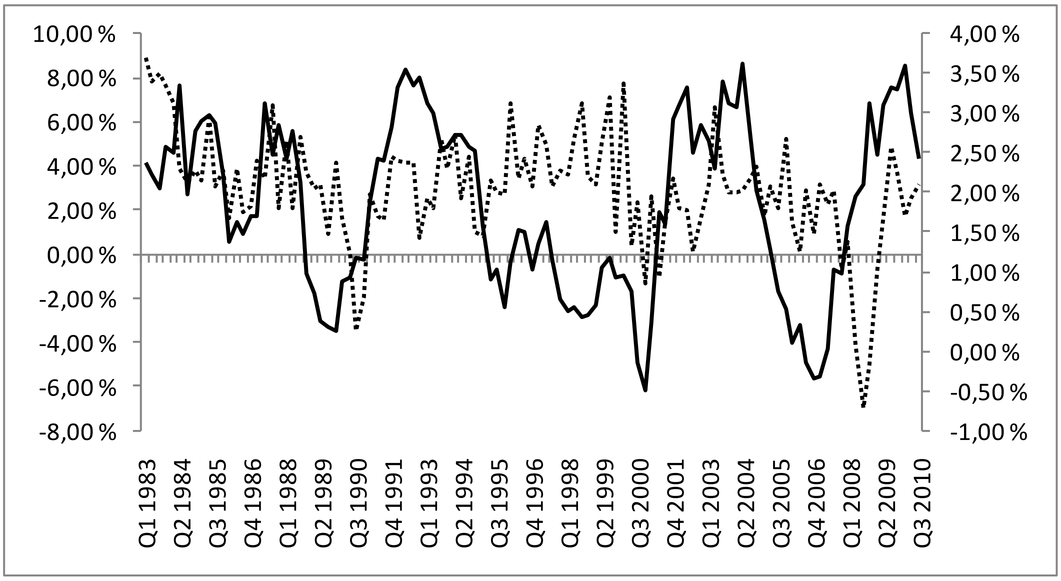
where ,r_2 is the rate on two-year securities, r_1 is the rate on one-year securities, $E(r_1)$ is the rate expected on one-year securities one year from now. Equation 2 states that for any choice of holding period, one should not expect to have different returns from holding different maturity dates. The long-term rates can be seen as weighted averages of the short-term bonds of rates.

Moneta (2005) states that, if the bond market is anticipating a recession it implies a decline in future interest rates, which means that long-term interest rates are going to decline as an effect from countercyclical monetary policy which is meant to stimulate the economy. Furthermore these lower rates reflect the lower rates of return and lower expectations of inflation during a recession. On the other hand, if the market participants are anticipating a boom in the economy, and high future rates of returns, then the expected future short rates are higher than the current short rates. This way the long-term yield should rise relative to short-term yields.

Another explanation is given by the monetary policy. When monetary policy is tightened, short-term rates rise more than the long-term interest rates. This leads to downward-sloping term structure. The tightening monetary policy can reduce spending, causing economic growth to slow down and the probability of a recession to increase. Estrella and Mishkin (1997) shows, that the monetary policy is a key determinant of the precise relationship between the term structure of interest rates and macroeconomic variables as inflation and total output.

Harvey (1988) gives the third explanation for the question why the slope of the yield curve contains relevant information about the future economic activity. This is based on the consumer choices. Assumption is that consumers prefer a stable level of income over the choice that income is very high during the expansion and very low during the recession. If consumers expect a reduction in their income, they prefer to save, thus buying long-term bonds in order to gain income in the recession. This increases the demand for the long-term bonds, which means that the yields in corresponding instruments will decline. Furthermore, investors may sell short-term bonds to finance this, so the yields in these will increase, hence when the recession is expected the yield curve flattens or even inverts.

Picture 1 shows the interest rate spread and the GDP development in United States over the last 27-years. As we can see from the picture, spread flattened in the last three recessions confirmed by the National Bureau of Economic Research (NBER) and inverted in two latest U.S. recessions.



— **=** *Yield Spread* - - - = *Change in real GDP*

Picture 1*. The annualized quarterly growth of the Real GDP in the U.S. and Interest rate spread from the years 1983 to 2010. The spread showed is the difference between Market yield on 10-year U.S. Government bonds and the Market yield on 3-month securities. Left y-axel is the % GDP development and right y-axel is the spread in %.*

Negative interest rate spread is usually referred as inverted yield curve. Usually the spread between long-term rates and short-term rates is positive and the yield curve has a positive slope, but when the market participants are expecting downturn in the economy and ultimately a recession the spread becomes negative and curve inverts. As explained above, when the rates for short-term are getting closer to the long-term rates and even exceeding them, the general interpretation for this is a signal of a recession. Table 2 shows the last 3 United States' recessions start and end months as well as the duration of each recession, announced by the NBER.

Table 2. Last Three Recessions in the U.S. and their Durations

Starting time of a recession	Ending time of a recession	Duration of a recession
December-07	June-09	18 months
March-01	November-01	8 months
July-90	March-91	8 months

In table 2 are shown the start month, the end month and the duration of three most recent recessions in the U.S. announced by the National Bureau of Economic Research.

Hamilton and Kim (2002) studied the yield curve and the reasons why it might contain information about the future output of the economy. They used a two-factor model of the term structure. This model can be divided to two factors, which can be interpreted as the current level of short-term rate and its volatility and expected changes in future short rates and the term premium. Hamilton and Kim (2002) explain the yield curve determinants; according to them the yield curve can be seen either as the financial markets expectation of future short rates or as the term premium. From this follows that the relationship can be explained either by the expectation effect which is the spreads role as a signal of the expected short-term rates, or as a term premium effect, which signals the change in the term premium.

As mentioned before the spread signals the expectations of the short rates and that way can give us a hint of what may happen in the future. The other factor was the term spread premium. According to Hamilton and Kim (2002) the term premium reflects in part of the risk of alternative investment. If interest rates become more volatile at the end of the expansion phase, this could have a reducing effect in the spread. The long rate might fall more than the short rate at the end of the expansion, because of the cyclical volatility warrants and a change in the risk premium, not because the expectation of the fall in the short rates.

Hamilton and Kim (2002) decomposed the spreads forecasting ability in to an expectations effect and a term premium effect, to get an idea which term accounts for the correlation seen between the GDP development and the yield spread.

The yield spread can be decomposed into two terms, which both may explain the forecasting power of the yield spread. Hamilton and Kim (2002) provide a mathematical formula for this, which is expressed in equation 3. According to Hamilton and Kim (2002) the term premium can be seen as the sum of a liquidity premium (n_t) and a risk premium ($\emptyset_t$) ($TP_t = n_t + \emptyset_t$).

$$yield\ spread = \left(\frac{1}{n} \sum_{j=0}^{n-1} E_t i_{t+j}^1 - i_t^1 \right) + TP_t \tag{3}$$

Where yield spread is the difference between long-term and short-term rate. The first term on the right hand side gives the difference between expected short-term rates over the next n periods and the current short-term rate. The second term on the right hand side is the term premium which is time-varying.

As explained in many studies and generally in academic literature, a fall in the spread predicts that the growth is going to slow down. If in fact a flattening in the yield spread predicts recession, it could be because: one, a temporarily high short-term rate suggest that recession is ahead, or because a fall in the premium on long-term bonds relative to short-term bonds suggests a slowdown in the economy. Short-term rate rises relative to the long-term rate prior to a recession, we face to questions: To what extend is this because of the rationally expected fall in the future short-term rates (expectations hypothesis) and what extend is it because of the foreseeable excess yield form holding long-term bonds has fallen (risk premium or liquidity premium).

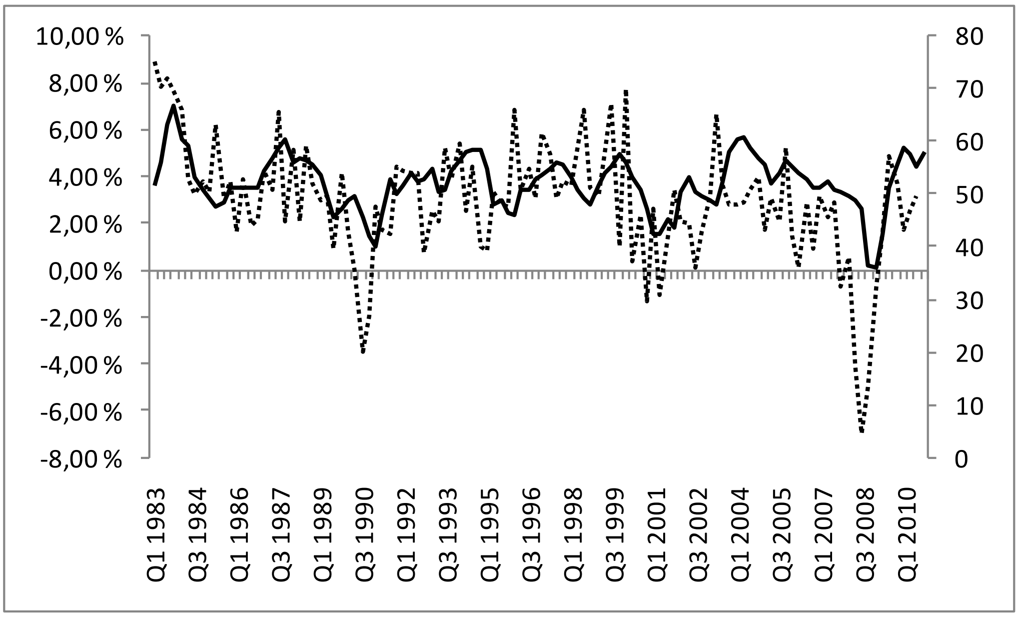
Hamilton and Kim (2002) answered to these questions in their empirical study. Their conclusion was that both of the factors, the expectations hypothesis and the time-varying term premium helped to predict total GDP growth up to 8 quarters ahead and both factors were also statistically significant. When determining which factor contributed more to the prediction they concluded that the short-term rate contribution in the prediction of the total GDP growth was statistically significantly bigger than that of the term premium. The expectations factor was more important factor quantitatively and statistically. Hence, the most important reason for the prediction ability of the yield spread is that a low spread implies falling future short-term rates.

Hamilton and Kim (2002) also developed a theoretical model to investigate the effect of the interest rate volatility on the term structure. This was done to see if the cyclical variation has something to do with the forecasting ability of the spread and term premium. The model was based on the time-variation in the variance of short-term interest rates. According to Hamilton and Kim (2002), the model suggests that an increase in interest rate volatility at the end of an expansion could provide a reason why the spread and term premium fall at the end of the expansion. Hamilton and Kim (2002) find that volatility is an empirically important determinant of both factors and a useful predictor of future interest rates. In spite of this, Hamilton and Kim (2002) founded that cyclical movements in volatility appeared to be unable to explain the reason why the spread and the term premium are useful measures in GDP forecasting.

2.2.2 Purchasing Managers Index

Purchasing Managers Index (PMI) is an index which is released monthly by the Institute for Supply Management (ISM). The ISM sends a question form to purchasing managers across the U.S. and based on their responses the ISM combines an index called PMI. Supply managers are facing a series of questions considering their firms' employment inventories, order backlogs, production, new export orders and imports of materials and supplies. Executives are asked whether or not the variables current level is higher or lower or the same as in the previous month. The index is calculated by taking the number of firms which report higher values and those who reports unchanged levels. This way the ISM creates a diffusion index for each variable. Thus, an index which reading is above 50 indicates that more executives are reporting better values for that variable. The higher the reading of the index is the greater amount of positive responses was given. The PMI is the combination of the following indexes: New Orders (30 %), Production (25 %), Employment (20 %), Supplier Deliveries (15 %) and Inventories (10%). (Koenig 2002)

The PMI is released monthly and this way it can provide an early reading on chances in the economy. The Institute for Supply Management states that a PMI reading above 50 indicates that the manufacturing sector of the economy is, in general, expanding. In terms of the GDP a reading above 42.7 indicates that the overall gross product in the economy is expanding. Koenig (2002) studied the PMI's prediction power and based on his regression model the reading over 40 signals expansion in the economy as a whole. Hence, the critical value for prediction considering the GDP growth should be considered 40, according to Koenig (2002). Picture 2 shows the PMI and GDP quarterly changes from 1983 to 2010.



—= *PMI* - - - = *Change in real GDP*

Picture 2. *The quarterly development of U.S. Purchasing Managers Index (PMI) and annualized change in real GDP from 1983 to 2010 Left y-axel is the % GDP development and right y-axel is the level of the PMI.*

We can see from picture 2 that PMI has not been able to lead real economy changes as well as yield spread, and when concentrating to recession reactions and signals the PMI seems to be reacting late.

In contrast, as mentioned earlier, table 2 provides the starting months of the last three recessions in the U.S. confirmed by the NBER. As one can see the PMI, was not really able to give an early warning about the recession, on the other hand from it one would have been able to tell that U.S. actually were in a recession before the NBER announced it, since the NBER does not announce the first official estimates of the each quarters GDP until a full month after the quarter end. (Koenig 2002)

2.2.3 Consumer Confidence Index

The U.S. Consumer Confidence Index receives plenty of coverage in both popular and financial press, not only in the U.S. but around the world. This index is reported in the way as if it would give a good indication about consumer spending. Consumer Confidence Index is considered to be a lagging indicator, which means that this indicator response after the economy is already changed. However, this indicator may tell us if recession is ongoing and whether or not we can expect it to go on. So the importance of this economical indicator becomes form the ability to signal positive or negative expectations about the consumer spending and the economy. This is why we wanted to examine how well this index has worked historically as an indicator for the economic turns and if this index would have been able to give warning signals, in time, about the recession. Furthermore we wanted to examine if Consumer Confidence Index had worked as an indicator of stock market development.

Consumer Confidence Indexes are produced by the conference board. It was first produce in 1969 and since 1977 it has been published on a monthly basis. The board mails out a sample around middle of the month to 5000 randomly selected individuals. The sample contains questions, presented in table 3. (Batchelor and Dua 1998)

Table 3. Conference Board`s Questions

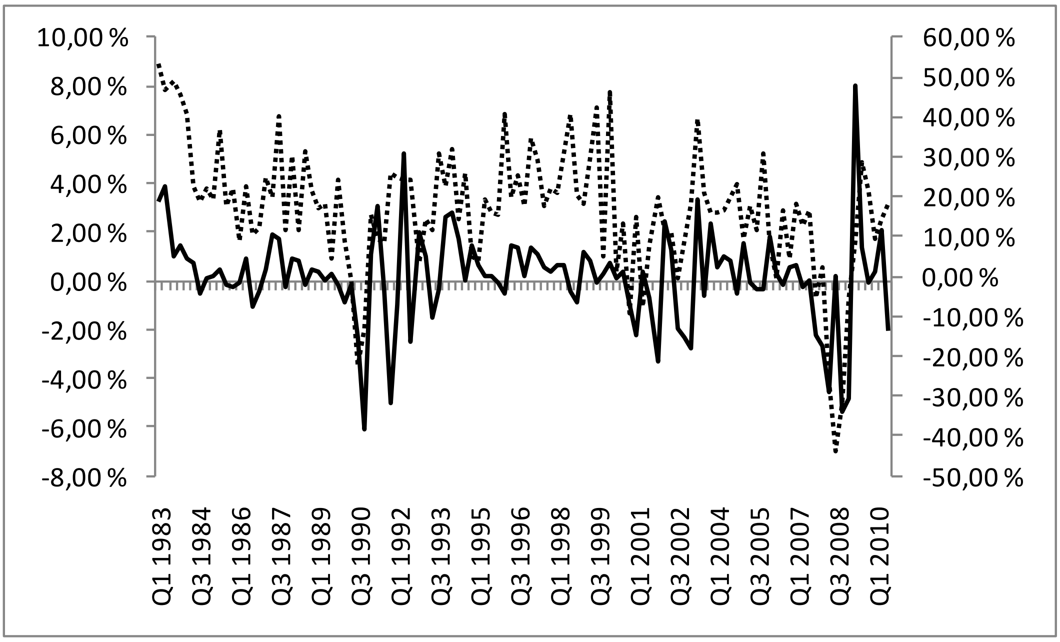
Question	Answer choices
How would you rate the present general business conditions in your area?	Good Normal Bad
Six months from now, do you think they will be?	Better Same Worse
What would you say about available jobs in your area right now?	Plenty Not so many hard to get
Six months from now, do you think there will be?	More Same Fewer
How would you guess your total family income to be six months from now?	Higher same lower

Table 3 presents the question from which conference board sent to individual consumers.

Usually about 1500 questionnaires are not returned, thus about 3500 are answered. Percentage answers are turned into figures for the positive answer balance to each question. Then these balances are averaged over all questions and expressed as an index, which gives the overall Consumer Confidence Index (CCI). The balance for the questions number 1 and 3 yield a present situation index (CP) and questions 2, 4 and 5 yield an expectations index (CE). (Batchelor and Dua 1998)

Consumer Confidence Index measures the health of the U.S. economy from the consumer's point of view. The index is based on believes and expectations about the future and current state of the economy as a whole as well as their own personal situation. The Consumer Confidence Index is a combined index of two indices. 40 % of the index is measuring consumers' current confidence (present situation index) and 60 % of the index is measuring consumers' expectations about the future (expectations index). (Consumer Confidence Survey® Technical Note 2011)

Picture 3 below, presents the quarterly development of the Consumer Confidence Index and GDP.



***—=** CCI* *- - - = Change in real GDP*

Picture 3. *The quarterly development of U.S. Consumer Confidence Index (CCI) and GDP from 1983 to 2010. Left y-axel is the % GDP development and right y-axel is the change in CCI in %*

As we can see from picture 3, The CCI has not been leading the GDP as much as yield spread. When concentrating recessions, it seems that CCI has been able to give some warning before the real economy starts its downhill, since it has gone negative before the actual recession. Naturally in recession the CCI takes its biggest dives.

2.3 Technical Analysis

Technical analysis based methods are used to predict stock market turning points. Technical analysis can be used in making investment decisions considering individual stocks or when considering stock indices as a whole, the same method applies. In comparison to fundamental analysis, the fundaments for individual stocks are a bit different than for the stock markets as a whole. For example, each firm has its own price to earnings ratio, which can be used when evaluating stocks “fair” market value by comparing it to industry average etc. Stock index is more of an indicator for the economy as whole and fundamental analysis for it needs to be based on the macroeconomic indicators and factors.

Technical analysis has faced contradictory debate in academic literature, some market participants believe its ability to predict future trends in markets but one could argue that markets' efficiency is in weak-form efficiency and one cannot profit consistently from technical analysis. Nevertheless the methods are out there and even though there are studies for and against of technical analysis, as shown in chapter 1.4 "related literature", the debate for technical analyze is far from over.

Appel (2003) defines technical analysis as a common term for methods, which are used when trying to determine the future trends in stock markets. Not by using a fundamental data, but using the actions and movements of the stock markets itself. An analyst who believes the power of technical analyze, believes that the actions of the stock market includes combined information of all investors and that these actions and movements of the stock markets can be used to predict future movements in the stock markets. There are many tools and models which can be used when performing technical analysis. Analyst can look for example patterns of trading volume, measures of the numbers of stocks rising and falling each day, and price movements. Many tools are quite exotic and even complex to use. According to Appel (2003), the simpler methods are usually the best. In following chapters we are introducing a few rather simple methods to perform technical analysis and explaining the theory and interpretations of the models used in this study.

2.3.1 Moving Average (MA)

Mills (1997) explains the Moving Average (MA) trading rule. It involves two moving averages of the level of the particular index. The short moving average of order n, which is presented in equation 4, and the long moving average of order m, presented in equation 5.

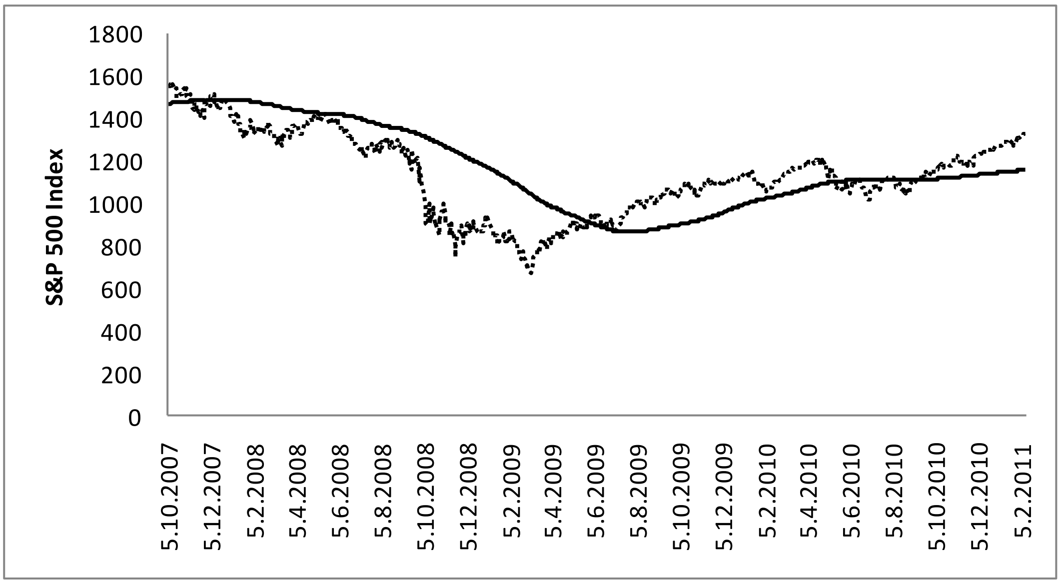
$$S_t\,(n) \;=\; \frac{1}{n}\sum_{i=0}^{n-1} x_{t-i} \tag{4}$$

Where, S_t is the short-term moving average, n is the order for short-term, e.g.1, x_t is the particular index e.g. S&P 500. Order m is always larger than order n. $m > n$

$$L_t\ (m) = \frac{1}{m}\sum_{i=0}^{m-1} x_{t-i} \tag{5}$$

The moving average trading rule generates a buy signal when short-term moving average rises above the long-term and a sell signal is generated when the short-term falls below the long-term moving average. When this happens a trend is initiated in the stock market. (Mills 1997)

According to Mills (1997), the most popular rule is 1-200, rule. This means that n is set to be 1; hence the short-term is just the current level of a particular index. Mills (1997) also tells that trading rules generated by the moving average, are often modified by a band around the moving average. This reduces the number of signals by eliminating signals referred to “whiplash”, which occurs when short- and long-term moving average are close to each other. This band can be e.g. 1 %. This way the buy or sell signal is generated only if the short-term moving average is more than 1 % above or below the long-term moving average. (Mills 1997)



—= 200-day moving average *- - - = 1-day moving average*

Picture 4. *An example of moving average graph. (S&P 500 index, daily data, 1-200 rule, from October 2007 to end of 2010)*

Picture 4 presents an example of a moving average graph. The 1-200 rule is applied in this example and the example is constructed by using S&P 500 total return index data from 10/2007 to end of 2010.

2.3.2 Moving Average Convergence-Divergence (MACD)

The Moving Average Convergence-Divergence was first introduced by Gerald Appel in 1978. Chong and Ng (2008) explains that the MACD is based on two exponential moving averages (EMA): short-term EMA and long-term EMA. The EMA at time t is defined by formula, which is presented in equation 6.

$$EMA_t = \left[\frac{2}{n} \times (P_t - EMA_{t-1})\right] + EMA_{t-1} \tag{6}$$

Where EMA_t is the exponential moving average at time t, n is the number of periods for EMA and P_t is the closing price for the asset on day t. The initial EMA is the n-day moving average of the series. Appel (2003) explains MACD to have three moving averages: 1) The fast moving average, which normally ranges from 6-19 units, 2) The slow moving average, which is normally two or three times the length of the fast moving average and 3) the MACD level and signal line. The level is calculated by subtracting the level of the long-term (slow) moving average from the short-term (fast) moving average. The moving average of these MACD levels is the signal line. Appel (2003) gives a general rule, that moving average length of between 3 to 9 units may be employed to smooth daily signal line readings.

Appel (2003) provides general rules for the MACD buy-hold-sell signals. 1) If MACD readings are positive, rising and lie above their signal lines, trend is rising and market is bullish. 2) If MACD signals are positive, but not anymore rising and have fallen towards or lie below signal lines, the upward is coming to or has come to end. 3) If MACD readings are falling towards zero or are negative, then the market price trend is negative. 4) If MACD readings are negative, but are turning up; crossing to above the signal line, the stock market is probably recovering. According to Appel

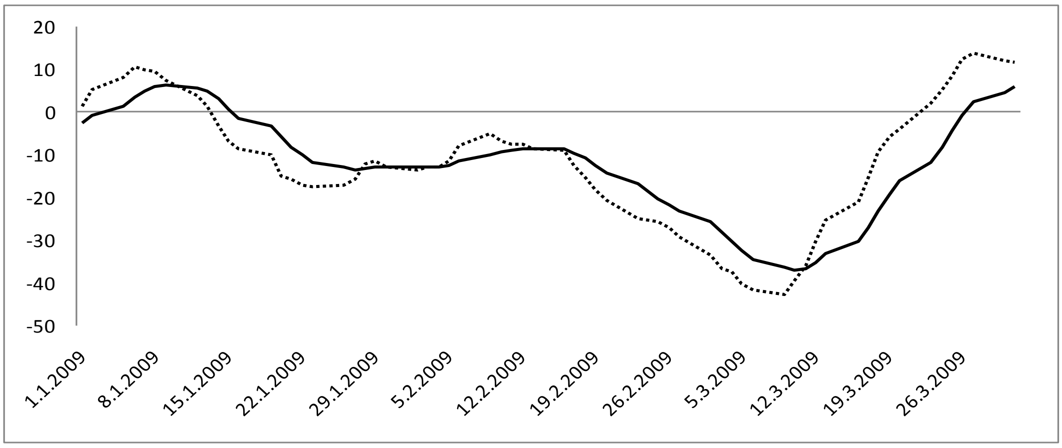
(2003) these four different scenarios identifies four stages for the stock market cycle.

Stage 1, Basing: Declines are complete and market is ready for the new upward movement.

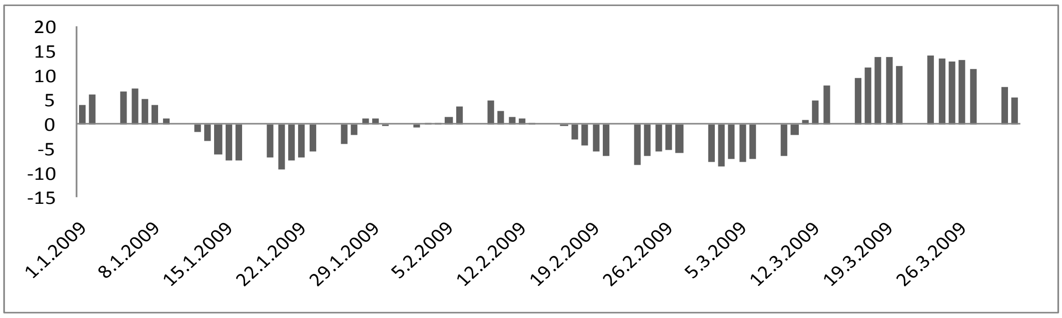
Stage 2, Advancing: The markets are rising, stock investing really pays off.

Stage 3, Topping: The stock market becomes more selective, this is the place to sell.

Stage 4, Declining: In this stage positions should be low and investor should get ready for the stage 1 again.



— = *9-EMA of MACD* - - - = *12/26 MACD*



■ = *Difference between MACD and the Signal line*

Picture 5. *An example of MACD graph and signal line histogram. (S&P 500 index, daily data, from the beginning of 2009 to the end of March 2009)*

Picture 5 presents both graphs used to describe the MACD. First graph is showing the relationship between MACD levels and its 9-units long Exponential Moving Average. This line is the signal line for the MACD. The second graph is showing the difference between MACD levels and the signal line. This histogram is used to describe only the points when MACD readings are above or below the signal line readings. The same information can be seen also from the first graph, but it is shown more clearly in the histogram.

2.3.3 Relative Strength Index (RSI)

The Relative Strength Index was first introduced in Commodities magazine (currently called Futures magazine) in June 1978 issue. It was introduced by J. Welles Wilder and he expanded the concept in his book "New Concepts in Technical Trading Systems". RSI is a momentum oscillator and it measures the speed and change of price movements. Since 1978 then the RSI has become one of the most popular technical indicators in use today. (Holter 2009)

The relative strength index is presented in equation 7.

$$RSI_t(n) = \frac{\sum_{i=0}^{n-1}(P_{t-i}-P_{t-i-1})1\{P_{t-i}>P_{t-i-1}\}}{\sum_{i=0}^{n-1}|P_{t-1}-P_{t-i-1}|} \times 100 \qquad (7)$$

Where RSI_t is relative strength index at time t, n is the number of periods and P is the price of the security (or the level of stock index). The term $1\{P_{t-i} > P_{t-i-1}\}$ is an indicator function. This equals one when the statement inside the brackets is true and when false it equals zero. The RSI has a range from 0 to 100. A security is considered to be overbought when its RSI is above 70. When its RSI is below 30 it is considered to be oversold. The RSI can also be used to determine the general trend in the markets; RSI readings above 50 are interpreted to indicate that the market is bullish and readings below 50 are interpreted to indicate that the market is bearish. (Chong and Ng 2008)

According to Chong and Ng (2008) the 14-day RSI, is a popular length for the period, utilized by traders. An example of a trading rule is also given by Chong and Ng (2008), a buy signal is triggered when RSI crosses the centre line from below and a sell signal is triggered when RSI crosses the centre line from above.

Picture 6. *An example of Relative Strength Index. (S&P 500 index, daily data, from the beginning of 2009 to the end of March 2009)*

In picture 6, is shown an example of the RSI graph. There are three lines in the graph and each of them presents an interpretation of RSI. When the RSI graph crosses the upper line (readings over 70) the security is considered to be over bought. When the index is below the lower line (readings below 30), the security is considered to be over sold. Middle line (readings at level 50) is used to determine the general trends in the market, and it also triggers above mentioned trading rules.

2.4 Instruments used in Hedging

2.4.1 Put options

Options are derivative instruments, this means that their values depends from the underlying assets. There are two types of options; Call options and Put options. Put option gives the holder the right to sell the underlying asset (e.g. stock) for the predetermined price and the seller (writer) of the option needs to pay such price for the asset. For this right the holder has to pay a margin for the seller, this is the price of an option. The purchaser of the put option believes (or is afraid) that the price of an asset is going to decrease in the future. (Hull 2006, pp. 181-183) If one owns a stock portfolio and believes, or predicts, that the stock market is going to decrease in short-term, one can hedge his portfolio with put options. When stock market decreases the gains from the options will cover the loss. The investor does not need to sell all of his stocks and face those transaction costs, or taxes from totalizing profits, just to protect one’s portfolio. This is discussed more in the 3.3. The price of a call option is determined by the equation 8 and price of a put option is determined by equation 9.

$$C = S_0 N(d_1) - Xe^{-rT} N(d_2)$$

$$d_1 = \frac{\ln(S_0 / X) + (r + \sigma^2 / 2)T}{\sigma\sqrt{T}} \tag{8}$$

$$d_2 = d_1 - \sigma\sqrt{T}$$

Where, C is the price of a call option, S is the spot price for the underlying asset, X is the options strike price, r is a continuously compounded risk-free rate, σ is the volatility of the underlying asset and T is the time to maturity of the option. (Hull 2006 pp. 295)

With equation 8 we can calculate the price for European call option, of which underlying asset does not pay dividends. From the call option price we can calculate also the European put option price by using the put-call parity, which is presented in equation 9. (Hull 2006, pp. 212-213)

$$C = P + S - Xe^{-rT}$$

$$P = C + Xe^{-rT} - S \tag{9}$$

Where, P is the price of a put option and other terms are the same as in equation 8.

From equation 8, we can see that the price of a put option depends from the maturity of the option, strike price and the volatility of the underlying asset. The only thing one does not know for sure is the volatility for the underlying asset for future; all the other terms can be observed from the markets.

2.5 Macroeconomic indicators ability to lead the Stock Market

For the macroeconomic indicators to work as a basis of the hedging strategy or warning system for downside risk of the stock market, they need to give their warning signals about the turning point of the economy and cyclical movement before the stock market does. As previous studies have covered (see e.g. Estrella and Mishkin (1998), Harvey (1991)), the stock market is also a leading indicator for GDP development and cyclical movements. This is the reason why it is important for macroeconomic indicators to give their signals before the stock market reacts to the risk of upcoming recession, so that the indicators have actual value for investor, in a stock market point of view. Previous academic literature has studied this relationship.

As mentioned in chapter 1.3, Cambell (1987) studied the relationship of the term structure and stock market returns. He found statistically significant evidence that there are predictable movements in excess returns on bills, bonds and stocks and that these movements are partially captured by a different term structure variables. Chen (1991) concluded that, among other macroeconomic variables, the term spread and the lagged industrial production growth rate were important determinants of future stock market returns. Furthermore he examined these variables ability to predict future market returns terms of their correlation with macroeconomic changes. His conclusion of this research was that variables ability to forecast the market returns relates to their ability to forecast recent and future growth in the economy.

The relationship between the consumers' confidence and stock market returns has been studied by Jansen and Nahuis (2003) and Fisher and Statman (2003). Both of these studies presented evidence that stock market development was able to forecast the changes in Consumer Confidence Index. Fisher and Statman (2003) found also that expectations component of the Conference Board confidence index had statistically significant relationship with Nasdag and small cap stocks in the following month, but the relationship with S&P 500 was not statistically significant.

3 DATA AND METHODOLOGY

3.1 Data

The data used in this study was retrieved from the Thomson one Banker Datastream. We use quarterly U.S. market data on different interest rate maturities from the years (1983-2010) and data on Purchasing Managers Index as well as Consumer Confidence Index. We also used quarterly data of U.S. GDP variation from the same years. This data was used in linear regression. Stock market data was also retrieved from Datastream. Data is the total return data from the S&P 500 index from the years (1999 – 2010).

We used stock market data both in comparison of the models and the strategies applied. Monthly data used to interpret indicators signals is also retrieved from datastream from the years 1999 to 2010. Summary statistics from the stock return data and macroeconomic indicators used in examination and comparison of the indicators' ability to warn about the crashes in last decade is presented in table 4. The returns are calculated by using natural logarithm. We selected the U.S. market, since it is the leading economy in the world and one of the most followed markets. It was also the breeding ground of the financial crises of 2008. Different types of data were also easily on hand from the U.S. market.

When examining the technical indicators, we used S&P 500 total return index daily and weekly data. These are however, only to build the strategies and indicators and the comparison is done on monthly basis from the data summarized above. We also used implied volatility data from S&P 500 put options from the years 1999-2010. This data was used to calculate the prices for 1 month at-the-money put options. These option margins are presenting the cost of hedging when indicators are signaling a crash.

Table 4. Summary Statistics of the S&P 500 total monthly return and Macroeconomic Indicators monthly data

	S&P 500	***Yield Spread***	***PMI***	***CCI***
Mean	-0.0823 %	1.8150 %	51.53	-0.5581 %
Standard Error	0.5243 %	0.1077 %	0.50	0.8670 %
Median	-0.0912 %	2.0976 %	52.30	-0.4700 %
Standard Deviation	6.1366 %	1.2608 %	5.85	10.1478 %
Sample Variance	0.3766 %	0.0159 %	34.24	1.0298 %
Kurtosis	1.3588	1.3103	0.5306	5.8041
Skewness	-0.4091	-0.3022	-0.7986	-0.2904
Range	35.1319 %	4.1166 %	28.10	87.5545 %
Minimum	-19.8818 %	-0.4924 %	33.30	-45.8990 %
Maximum	15.2501 %	3.6242 %	61.40	41.6556 %
Count	137	137	137	137

Summary statistics of the S&P 500 index and macroeconomic indicators monthly data from time period of August 1999 to the end of year 2010. Yield Spread = Difference between Market yield on 10-year U.S. Government bonds and the Market yield on 3-month securities. PMI = Purchasing Managers Index. CCI = Consumer Confidence Index.

In table 4, average is the average total monthly return of the S&P 500 index, yield spread, Purchasing Managers Index and Consumer Confidence Index from our investment period (August 1999-2010). As one can see the average monthly return of S&P 500 is not something which one would describe as impressing. During this time period there were two recessions in U.S. economy, first in 2001 and the second from December 2007 to midway of 2009. The second interesting statistic from table 4 is the standard deviation of the returns which is a little over 6 % per month, which translates into approximately 21 % annualized standard deviation. Kurtosis and skewness describes how the returns behave in comparison with the normal distribution (Vaihekoski 2002, pp. 169). The S&P 500 index's total monthly return does not differ from normal distribution in terms of kurtosis, since it is not over 3. Same applies with yield spread and PMI. CCI's kurtosis differs from normal distribution in terms of the monthly change in investing period. (Vaihekoski 2002, pp. 169). There are findings in academic research that stock index returns are negatively skew

(Vaihekoski 2002, pp. 169). This is the case also with our S&P 500 data. Interesting statistics are also the minimum and maximum total monthly returns. Minimum for S&P 500 is over 19 % negative in one month and maximum is 15 % gain in one month. The spread in interest rates were almost 5 % negative and maximum spread over the investing period was 3.6 %. The biggest negative change in CCI was over 40 % and upward direction in one month was also over 40 % in selected time period.

We had to have two different time periods in empirical testing (Linear model had a time period from 1983 to 2010 and comparison of the hedging strategies had a time period from 1999-2010), since GDP data is quarterly data and to have enough observations and to cover last three recessions the timeframe had to be longer. Why the investment period is only from the August of year 1999 is because option data available for us does not go back longer than that. The S&P 500 index total return data was only used in comparison of the strategies and to evaluate the effect of the hedge based of the indicators signals. GDP data and linear regression was used only when establishing the explanatory power of the macroeconomic indicators of the future GDP development and its statistical significance. The investing period of last decade, is an example of how an equity investor could use the information that macroeconomic indicators contains from the GDP development and uses signals from macroeconomic indicators which are interpreted to signal a turn in real economy. The investing period also provides us means to compare different indicators and hedging strategies in numerical way e.g. in terms of profit.

The Data we used in our in-sample estimation of the U.S. GDP changes was quarterly data from the years 1984-2010. Explanatory variables were naturally also quarterly data. We did several regressions to find out how much yield spread was able to lead GDP changes. The biggest R-square came when k was set to 6. This is of course in-sample and no one could know how much the yield spread is able to lead the GDP in the future, but in our research period the lag seems to be approximately 18 months. This result is in line with the previous academic literature, where yield spread has been able to predict recession approximately 4 to 8 quarters ahead. (See e.g. Estrella and Mishkin 1998 and Hamilton and Kim 2002). With CCI and PMI the lag was set to be one quarter since they did not seem to lead the GDP as much as the yield spread. The yield spread data was from the years 1983-2010, and with PMI and CCI we used data from years 1984-2010, since the lag employed was smaller. The GDP changes explained were from Q3/1984 to Q3/2010 and data to explain the changes with yield spread was from Q1/1983 to Q1/2009 and with PMI and CCI from Q2/1984 to Q2/2010.

3.2 Methodology

3.2.1 Ordinary Least Square Estimates (OLS)

Ordinary Least Square Estimates is a classic linear regression model. According to Brooks (2008, pp 27) a regression is an attempt to explain movements in a variable by reference to movements in one or more other variables. In other words regression model is used to find out if movements in variable y can be explained by the movements of other variables, x1, x2 and so on. The model can be used to find out in to what extend these other variables can explain the variations in variable y. The general from for the OLS model is expressed in equation 10 in the chapter “Linear model”.

Brooks (2008 pp.131-160) explains the OLS model’s assumptions, so that hypothesis tests considering the coefficients estimates are conducted validly. These assumptions are:

1. $E(u_t) = 0$, *Average value of the errors is zero*

2. $var(u_t) = \sigma^2 < \infty = var(u_t) = \Omega$, *The variance of the error terms are homoscedastic*

3. $cov(u_i, u_j) = 0$, *Covariance between the error terms over time is zero*

4. $cov(u_t, x_t) = 0$, *The x_t are non-stochastic*

5. $u_t \sim N(0, \sigma^2)$, *The disturbances are normally distributed*

According to Brooks (2008) assumption 1 is never violated, in the regression equation. When considering the 4th assumption, the OLS estimator is consistent and unbiased in the presence of stochastic regressors, when the regressors are not correlated with the error term of the estimated equation. Since assumption 1 holds, the estimator is still unbiased, even if the regressors are stochastic. (Brooks 2008, pp. 131-160)

3.2.2 Linear model

The linear forecasting model is based on a simple linear regression which contains only one variable (e.g. yield spread). This is a classical case of the simple linear regression model. Interest rate spread based forecasting model was implemented by Harvey (1989 and 1991) same model has been used in many academic studies (e.g. Duarte et.al. 2005). The model contains a single equation and, as said above, contains only one forecasting variable. The equation for the linear forecasting model is described in equation 10.

$$\Delta GDP_t = \alpha + \beta X_{t-k} + u_t \tag{10}$$

Where:

ΔGDP = Growth in total (annual) GDP from quarter t-k to quarter t

X_t = Explanatory variable observed at time t-k

u = The forecasting error, which cannot be anticipated. This can be used to assess the accuracy of the forecasting model

α and β = estimated coefficients (intercept and slope)

According to Zeileis (2010) equation 10 can generally present as:

$$y = X\beta + \ u_t \tag{11}$$

Harvey (1991) shows that the coefficients α and β can be estimated by using linear regression. The t-statistics of the coefficients however are more complicated. This is because the variable to be forecasted is overlapping. The t-statistics can be corrected by using a technique introduced by Newey and West (1987), more on this in chapter 3.2.6.

Assumptions presented above apply to the classical linear regression model presented in equation 10. As mentioned above the coefficients can be estimated with the OLS estimator β with corresponding OLS residuals u.

Zeileis (2010) derived coefficient and residual as follows:

$$\hat{\beta} = (X^t X)^{-1} X^t y \tag{12}$$

$$\hat{u} = (l_n - H)u = (l_n - X(X^t X)^{-1} X^t)u \tag{13}$$

Where l_n is the n-dimensional identity matrix and according to Zeileis (2010) H is commonly called as “hat matrix”. The estimates which linear regression gives are unbiased and asymptotically normal. Zeileis (2010) explains two ways to describe the covariance matrix (Ψ) of linear regression estimates:

$$\Psi = \sigma^2 (\hat{\beta}) = (X^t X)^{-1} X^t \, \Omega X (X^t X)^{-1} \tag{14}$$

and above equals:

$$= \left(\frac{1}{n} X^t X\right)^{-1} \frac{1}{n} \Phi \left(\frac{1}{n} X^t X\right)^{-1} \tag{15}$$

Where Ψ is the covariance matrix of the estimates and, Φ = $n^{-1} X^t \, \Omega X$ is essentially the covariance matrix of the estimate function $V_i\,(\beta) = x_i(y_i - x_i\beta)$. The estimating functions evaluated at the parameter estimates have then sum zero. When considering above in the context of classical linear regression model, it is crucial to have a consistent estimator for covariance matrix. The estimator which is used depends on the assumptions made considering the estimates. The linear regression presented in equation 10 can be extended to multiple linear regression with more than one explanatory variable. The equation takes following form:

$$\Delta GDP_t = \alpha + \beta_1 \beta X_{1t-k} + \beta_2 \beta X_{2t-k} \ldots \beta_k \beta X_{kt-k} + u_t \quad (16)$$

Where, ΔGDP is the Growth in total (annual) GDP from quarter t+k. k is the number of lags. $X_{1t,}$ $X_{2t,}\ldots X_{kt,}$ are the Explanatory variables observed at time t. u is the residual and α and β are estimated coefficients.

3.2.3 t-statistic

Brooks (2008, pp 65-66) explains the t-statistic to be as a ratio of the coefficient to its standard error. This is expressed in equation 17.

$$t - statistic = \frac{\beta}{SE(\beta)} \quad (17)$$

Where β is the coefficient of the regression model and SE is its standard error. The null hypothesis of the t-statistic test is that the coefficient β is zero, if this is true and the null hypothesis is not rejected, the coefficient does not statistically differ from zero, although the test might show some different number for the coefficient. If however, the null hypothesis is rejected, the coefficient does statistically differ from zero and the coefficient is statistically significant. According to Brooks (2008, pp 66) Values for the t-statistic test are compared with the appropriate critical value from a t-distribution. Rejecting or not rejecting the null hypothesis of the test derives from the choice of critical value, i.e. 5 %. The two sided 5 % critical value is approximately ± 2, so as a rule of thumb the model is statistically significant when the t-statistic exceeds 2 in absolute value.

3.2.4 Heteroscedasticity

As mentioned in chapter 3.2.1 the OLS contains an assumption of homoscedasticity. When the variance of the error terms is not constant the assumption does not hold and error terms are said to be heteroscedastic. What if this assumption of violation is ignored? According to Brooks (2008, pp. 135) OLS estimators will still give unbiased coefficient estimates, but they are no longer BLUE (Best Linear Unbiased Estimator), hence they do not have the minimum variance among the class of unbiased estimators. If the error terms are heteroscedastic, the formula for the coefficient standard errors does not hold. In other words, if the error terms are in fact heteroscedastic the standard errors could be wrong and as pointed out in equation 17, the standard error is in play when determine the t-statistic for the coefficient. This way it affects the determination of statistical significance and in the presence of heteroscedasticity the whole interpretation of the model could be wrong.

3.2.5 Autocorrelation

An assumption is made regarding to classical linear regression model, is explained by Brooks (2008, pp. 139-149). This is the assumption that error terms are uncorrelated with one another, that is that the covariance between the error terms over time is zero. If this is untrue it is said that error terms are autocorrelated. There are tests to see if error terms (residuals) are autocorrelated, for example Durbin-Watson (DW) test and Breusch–Godfrey test.

According to Brooks (2008, pp. 149), if autocorrelation is present and it is ignored the effects are quite similar to those in presence of heteroscedasticity. The coefficients are not efficient; hence the standard error estimates could be wrong. This means that the statistical significance may also be interpreted wrongly. For example positive autocorrelation means that the OLS standard error estimates will be biased downwards in relation to their true values. That means that the OLS model will understate their true variability. R^2 is also likely to be inflated in relation to its true value, when residuals are autocorrelated and this is ignored.

3.2.6 Correction to t-statistics calculation in presence of heteroscedasticity and autocorrelation

If the results are autocorrelated or heteroscedastic it raises issues described above. This naturally affects the conventional t-statistics and therefore the t-statistics need to be calculated differently. In the presence of autocorrelation and/or heteroscedasticity the t-statistics can be calculated by using technique introduced by Newey and West (1987). According to Zeileis (2010) this problem can be taken care of with heteroscedasticity consistent (HC) and heteroskedasticity and autocorrelation consistent (HAC) covariance matrix estimators, these estimators plug an estimate $\widehat{\Omega}$ or $\widehat{\Phi}$ in equations 14 and 15 respectively. These estimates are consistent in the presence of heteroscedasticity and autocorrelation respectively. (Zeleis 2010)

Heteroscedasticity typically arises with cross-sectional data. Its Covariance matrix is diagonal but it has nonconstant diagonal elements. This is the reason why various HC estimators have been suggested in econometrical literature and research. These estimators are build by plugging an estimate of type $\hat{\Omega} = diag\ (\omega 1, \omega 2 \ldots, \omega n)$ into equation 14. The difference between the estimators comes from the choice of the ωi. (Zeleis 2010)

If the residuals are autocorrelated and heteroscedastic, the calculation of the t-statistics without a HAC estimator could be misleading. If the form of autocorrelation and heteroscedasticity is unknown the solution is to estimate the term Φ. HAC estimators do just that and HAC covariance matrix is constructed by plugging an estimate of $\widehat{\Phi}$ in equation 15 which was presented earlier. $\widehat{\Phi}$ is presented in equation 18.

$$\widehat{\Phi} = \frac{1}{n} \sum_{i,j=1}^{n} \omega|i-j|\ \widehat{V}_i \widehat{V}_j^t \tag{18}$$

Where, $(\omega_0, \omega_1 \ldots, \omega_{n-1})^t$ is a vector of weights. The question what the weights should be is studied in academic literature for example by Newey and West (1987) and (1994) and Andrews (1991). Andrews placed the choices of weights in a framework of choosing the weights by kernel functions with automatic bandwidth selection. Newey-West technique to calculate significance levels in presence of heteroscedasticity and autocorrelation is available in statistical programs such as WinRats.

3.2.7 In-sample vs. out-of-sample forecasts

In sample forecast means a forecast which is made for the same data set, which was used to estimate the forecast model and its parameters. In other words the estimation uses data which actually would not be available in real forecasting situation. This is why it is vital to evaluate the models ability to predict changes in out-of-sample scenario, where some observations are hold back from the estimation model. (Brooks 2008, pp. 245) Using the in-sample estimation we can observe how well have parameters been able to explain the variance in dependent variable during the whole sample period, but this model can't be used to forecast changes in sample period, since it uses data which wouldn't have been available when the forecasting was made.

3.3 Hedging Strategies and Calculations

3.3.1 Hedging Strategies

A part of our empirical research is a comparison of the different indicators based hedging strategies. In this part we examine and compare how would hedging strategies based on macroeconomic and technical analysis indicators worked in selected time period, which was the last decade. This time period was characterized by two recessions in the U.S. in 2001 and 2007. The examination is executed with back testing of different indicators based hedging strategies. All of the strategies are based on the same question; when one should start a hedge of a portfolio and when to stop it?

In these strategies we do not buy or sell index shares, we just buy put options when the indicator predicts downhill for the stock market or in the case of our macroeconomic indicators, the overall U.S. economy. This means that all of the strategies are based on the indicators and the indicators ability to predict the downside risk is the only difference among the strategies. This means that examined strategies have very similar average monthly returns over the whole time period, since only the months, where the indicator is signaling the hedge are different among the strategies. The whole return over the time period and annualized returns over the time period however shows the difference among the indicators usefulness for investor.

These imaginary portfolios are assumed to be well diversified portfolios whose beta is one. This means that the return of these portfolios mirror those from the index. We further assume that the dividend yield is the same as from the index. (Hull 2006, pp 318). Besides the warning from the indicators and hedging the portfolio based on them, all strategies are very passive and besides the profits (or losses) from option positions, imitates the profits from the buy-and-hold strategy. Since the examined time period is over 10 years and the frequency of the trade is one month, the average monthly returns are almost same with every hedging strategy and with the buy-and-hold strategy. Since these strategies try to eliminate the downside risk and the effect of the crash on the index, months when markets were reacting to the threat make all the difference in the world, when it comes to the performance evaluation of the strategies, even thought the average monthly returns over the period were almost identical among the strategies.

There are a few reason for hedging, thus use of the put options, rather than selling the whole portfolio when anticipating a crash. First, there are taxation issues. If one would sell his or hers whole portfolio, one would need to pay taxes for the realized profits and after the crash there would not be as much cash to buy the portfolio back. Second reason is the transaction costs. Transaction costs are often a percentage of the trade. If one would sell and then again buy a whole portfolio, the dollar amount of the transaction cost would be much larger than it is when buying put options for that portfolio (Hull 2006, pp 65). The third reason derives from the features of an option. If the indicator is signaling a crash or a downhill in the stock market or a recession in the overall economy, but this does not happen an option will give the possibility to gain from the rise in the stock market since one does not need to exercise the right to sell. With an option you only lose the margin, which can be thought as a cost of the hedge. If one would sell his or hers whole portfolio, the cost of the hedge does not have dollar amount, but on the other hand it can be much severe, since investor will lose the opportunity of the rise in the stock market.

3.3.2 Stock Returns and Option Margin calculations

The stock market returns are calculated from S&P 500 total return index data, described in table 4. Time period was from August 1999 to the end of 2010. Data range was one month and returns were calculated with natural logarithm, as shown in equation 19, so the returns were logarithm total returns.

$$r = ln\frac{p_t}{p_{t-1}} \tag{19}$$

Where r is the return, p_t is the index level at time t, and p_{t-1} is the index level at time t-1. This way we can calculate the returns for the buy and hold strategy and naturally, for our imaginary index portfolio. Logarithm returns are also used when calculating volatility and risk adjusted performance of the strategies.

The volatility is the standard deviation of the returns (Vaihekoski 2002). This way we have monthly volatility of the returns. This can be annualized by multiplying the monthly volatility by square root of 12, as presented in equation 20.

$$Annual\ volatility_t = monthly\ standard\ deviation_t\ x\ \sqrt{12} \tag{20}$$

The volatility describes how risky the investment is. In our case we can use the volatility to compare indicators in terms of the riskiness.

As mentioned in chapter 3.1, we used Datastream to retrieve our data. Unfortunately, historical option prices were not in our reach and we needed them in back testing of our different indicators and strategies based on them. Datastream gives implied volatilities for S&P 500 at-the-money options (ATM). The maturity for these options is 30 days. The Datastream calculates the implied volatility for these index options by interpolating the two options which has the nearest strike price for at-the-money level. From these implied volatilities we can calculate that ATM level for 1 month S&P 500 index options by using the Black-Scholes formula, which was presented in equation 8. This was done with Excel and the VBA formulas for option margin calculations are presented in appendix 14.

The amount of options needed to hedge the underlying portfolio was calculated as presented in equation 21.

$$\frac{V_t}{V_{ind,t} \times k} \tag{21}$$

Where $V_t$is the value of the portfolio at time t, and $V_{ind,t}$ is the level of the index at time t and k is the basket value coefficient, which tells us how many times each contract is on the index. In S&P 500 this is 100. (Hull 2006, pp. 318). With equation 21 we can calculate the number of options needed to hedge our imaginary portfolio. However accurately we could calculate the number of options needed to have a “locked” value to our portfolio, we faced a problem regarding our option data. We only have the ATM put options’ implied volatilities and we were able to calculate the margins only for those options, which exercise price was at-the-money level. This is the reason why the break-even level could not be reached and we could not actually “lock” the portfolio value at pre determinate level. This meant that we needed to face the risk of having negative returns for the total portfolio in months were the cost of hedging was more than the gain from options. However, this was the only way to calculate the prices and since we did not have data for out-of-the money options we could not do the comparison of the strategies with perfect hedge positions.

We also needed to calculate the total value of the portfolio. That is, the value of the index portfolio and the option positions. The value of option position was calculated as presented in equation 22.

$$-(P \times N \times k) + (X - V_{Ind}) \times (N * k) \tag{22}$$

Where, P is the margin of a put option, N is the number of options bought, X is the exercise price of an option and k is again the basket value coefficient. V_{Ind} is the level of the index at time of the maturity of an option. In equation 23 the term $-(P \times N \times k)$ calculates the cost of hedging and $(X - V_{Ind}) \times (N * k)$ calculates profit from option position. In addition to this we also added a transaction cost for acquiring the put options. The transaction cost is usually a fraction of the total trade. In this sense we applied an assumption of the transaction cost, which was 2 % of the trade in both ways (in buying and selling of the option position). This was done to see how the costs will affect in strategy where options are acquired more frequently.

The hedging was done always at the previous month index level. This was done because we wanted to avoid only the biggest downsides and see how well the indicators predicted them, not to lock the whole portfolio in to the beginning value. This gave the strategy the possibility to gain from the stock market rise. The hedging was rolled on if the indicator did not show a change for a better in the economic cycle or trend. With yield spread this generated a problem since it does not give a clear signal when the economic is turning for better, since it leads the cycle quite a lot.

With the hedging positions, we did not calculate the Greek letters, or maintained a delta neutral position. This was, because the purpose of the hedge was just to avoid the downside risk and to compare different indicators usefulness from investors' point of view in a practical example, not to trade options while doing it.

3.3.3 Risk adjusted Performance Ratio - The Sharpe's Ratio

The reward-to-variability ratio is a ratio used to measure the risk-return trade off of an investment. Sharpe measure is one of the reward-to-variability ratios that are commonly used to evaluate the performance of the portfolio against other investments. Bodie et.al. (2001) explains that Sharpe's ratio divides average excess return over the sample period by the standard deviation of returns over the same period. Sharpe's ratio measures the reward to total volatility trade-off. There are other performance ratios that can be used to compare the risk-return trade off, but Sharpe's ratio is the best choice when the portfolio represents ones entire risky investment fund. (Bodie et.al. 2001 pp. 812,815)

$$Sharpe\ Ratio = \frac{R_p - R_f}{\sigma_p} \tag{23}$$

where, R_p return of the portfolio, R_f is return of a risk free asset and σ_p is the volatility of the portfolio. We used Sharpe’s ratio to compare and evaluate the risk adjusted performance among our different strategies.

4 RESULTS

4.1 The Linear Model

The model used to determine whether or not our indicators have been able to explain changes in total output is a classical linear regression model (CLRM) or as before referred, Ordinary Least Squares Estimates (OLS). Academic literature has covered in several studies, that this kind of model with yield spread as explanatory variable has been very effective. On the other hand some studies published more recently have noted that its power to predict the changes in GDP has weakened, but is still effective. This is why we wanted to see how well the yield spread and other indicators have been able to explain the recent movements in U.S. GDP development. Our in-sample regression is presented in equation 24.

$$\Delta GDP_t = \alpha + \beta(Variable_{t-k}) + u_t \tag{24}$$

Where, as before, ΔGDP is the Growth in total (annual) GDP from quarter t. $Variable$ is one of the following: Difference between 10 year rate and 3 month annualized yields to maturity observed at time t-k. The quarterly change in Consumer Confidence Index expressed as a percentage change at time t-k or a level of the Purchaser Managers index at time t-k, where k is the number of lags employed. u is the residual and α and β are estimated coefficients. The yield spread was calculated with natural logarithm as presented in equation 25.

$$Yield\ Spread = ln\frac{1+rate\ for\ 10\ year\ rate}{1+rate\ for\ 3\ month\ rate} \tag{25}$$

4.2 In-Sample Estimation

When determining how well the macroeconomic indicators explains the changes in total output we needed to estimate them with a regression model. The model estimated determinants for the equation 24 and these are presented in table 5. As mentioned above; this was done as in-sample estimation. This means that these results cannot be used in back-testing of the model’s prediction power. Our goal in this estimation was only to see how well the indicators has explained the changes in recent history and our investment period, so that we could see if the indicator, and more importantly warning signals it generates, has been statistically significant in last 26 years, as Chen (1991) showed, macroeconomic variables ability to forecast the market returns relates to their ability to forecast recent and future growth in the economy. Our in-sample estimation's point was to establish the variables' ability to explain future changes in GDP in our selected research period not to predict GDP changes or to examine the prediction accuracy of the estimated model.

Table 5, shows the results of the in-sample estimation for macroeconomic indicators used in this study. All of the linear regressions had one explanatory variable, hence they were CLRM models. Table 5 contains all of the estimates of the macroeconomic indicators done with the CLRM.

Table 5. Parameter Estimates for the Linear Models

Regression	**I**	**II**	**III**
Intercepts	0.01277 2.98	0.02712 11.99	-0.03113 -1.27
Yield Spread	0.79561 3.83	-	-
CCI	-	0.06096 3.18	-
PMI	-	-	0.00112 2.38
Num. Of Obs.	104	104	104
Adj. R-Square	0.1163	0.0803	0.0428
F-Stat	14.68	10.80	5.65

Model: $\Delta GDP_t = \alpha + \beta(Variable_{t-k}) + u_t$ *, with quarterly data. First row shows the intercepts (α) of the linear model for each regression. After that there is shown the coefficients* (β) *for each variable respectively. The t-statistics are shown in second in each row. All of the variables were lagged with the value of k as follows:* $Yield\ Spread_{t-6}, CCI_{t-1}, PMI_{t-1}$*. Yield Spread = Difference between Market yield on 10-year U.S. Government bonds and the Market yield on 3-month securities. PMI = Purchasing Managers Index. CCI = Consumer Confidence Index.*

From table 5, we can see that our in-sample estimation is statistically significant for all of the indicators, since t-value is over 2 in absolute value. Only statistically not significant value is the intercept for PMI. The R-square tells us how much the explaining variable explains the changes of the explained variable. The adjusted R-square of the OLS for yield spread was 11.63 %, for CCI the adjusted R-square was 8.03 % and for PMI it was approximately 4.30 %. This means that yield spread has had explanatory power over GDP development. More importantly when looking picture 1 form the chapter 2.2.1 we can see that the negative spread leads the downfall in the GDP. The R-square does not tell is the explanatory variable estimating rise of fall, just the overall explanatory power, but we can see that negative spread has been effective signal of the recession and the variable's estimates are statistically significant. Still this does not mean that we are out of the woods just yet. We need to test our OLS test for autocorrelation and heteroscedasticity and see if our model has them and if, how does it change the significance level of our estimation. This is done in the next chapter.

4.3 Statistical Significance

For our results to actually be significant we need to investigate certain assumptions made in the linear regression, these were introduced in chapter 3.2.1. We tested these assumptions when constructing the linear regression. First we tested if our data was heteroscedastic. This test was made in SAS Enterprise Guide 4. The test which was used was the white test and its results for our macroeconomic indicators are provided in table 6. Table contains all different tests, which were done separately.

Table 6. Results for the Heteroscedasticity tests (the White test)

Variable	DF	Chi-Square	Pr > ChiSq
Yield Spread	2	11.42	0.0033
CCI	2	4.96	0.0838
PMI	2	5.01	0.0818

Table presents results for heteroscedasticity tests for used macroeconomic variables: Yield Spread = Difference between Market yield on 10-year U.S. Government bonds and the Market yield on 3-month securities. PMI = Purchasing Managers Index. CCI = Consumer Confidence Index.

As shown in table 6, our data for yield spread is heteroscedastic, since Pr > ChiSq is lower than chosen risk level of the test (0.05). This means that our calculations of the statistical significance considering yield spread are not reliable and we needed to do adjust the significant level calculations for yield spread to make sure that the model is in fact statistically significant. CCI and PMI data was homoscedastic since Pr > ChiSq was over the chosen risk level.

We also wanted to test the CLRM residuals for autocorrelation. The test used to detect autocorrelation was the Durbin-Watson test. The results for the Durbin-Watson test for each variable are shown in the table 7.

Table 7. Results for the Autocorrelation tests (Durbin-Watson)

Variable	Order	DW
Yield Spread	1	1.2588
CCI	1	1.3548
PMI	1	1.1964

Table presents the results for autocorrelation test for used macroeconomic variables. Yield Spread = Difference between Market yield on 10-year U.S. Government bonds and the Market yield on 3-month securities. PMI = Purchasing Managers Index. CCI = Consumer Confidence Index.

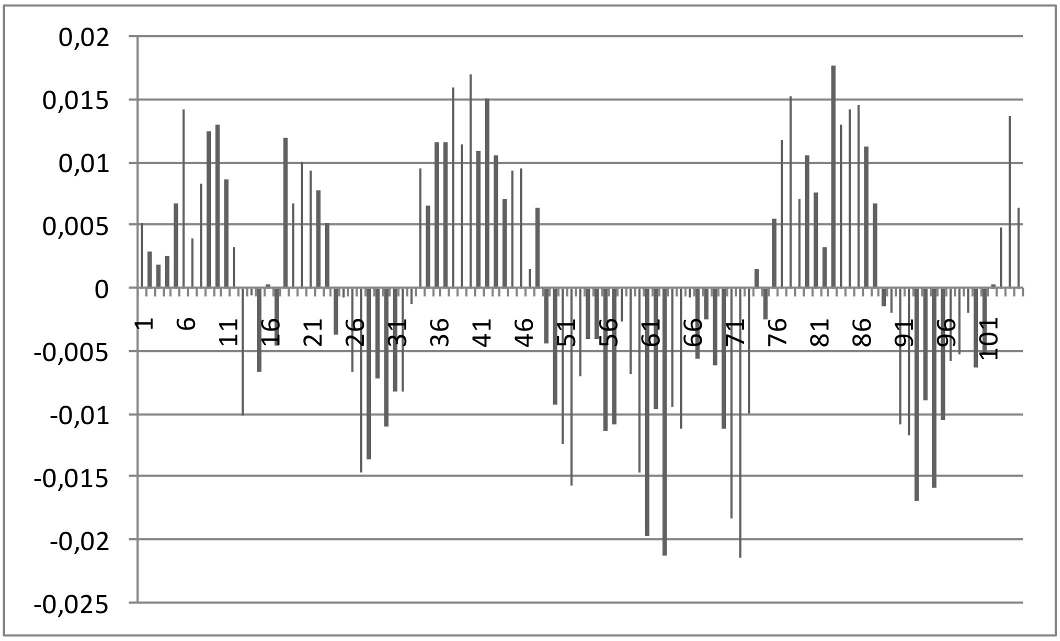
The interpretation from the autocorrelation test is that our linear regression residuals were autocorrelated in all of the CLRM tests, since the DW differs from 2. We confirmed the positive autocorrelation by making a test with SAS Enterprise Guide 4. These results are shown in table 8.

Table 8. Estimates of Autocorrelations

<table>
<tr><th>Variable</th><th>Lag</th><th>Covariance</th><th>Correlation</th><th>-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1</th></tr>
<tr><td>Yield Spread</td><td>0</td><td>0.000505</td><td>1.000000</td><td>| |********************|</td></tr>
<tr><td></td><td>1</td><td>0.000187</td><td>0.370555</td><td>| |******* |</td></tr>
<tr><td>CCI</td><td>0</td><td>0.000526</td><td>1.000000</td><td>| |********************|</td></tr>
<tr><td></td><td>1</td><td>0.000169</td><td>0.322423</td><td>| |****** |</td></tr>
<tr><td>PMI</td><td>0</td><td>0.000547</td><td>1.000000</td><td>| |********************|</td></tr>
<tr><td></td><td>1</td><td>0.000220</td><td>0.401703</td><td>| |******** |</td></tr>
</table>

Table presents the results for estimations of autocorrelations for used macroeconomic variables. Yield Spread = Difference between Market yield on 10-year U.S. Government bonds and the Market yield on 3-month securities. PMI = Purchasing Managers Index. CCI = Consumer Confidence Index.

One can see form table 8 that our linear models' residuals are positively autocorrelated. The probable cause for autocorrelation between the residuals derives from the data overlapping (Harvey 1991). We also contracted a histogram from the residuals for yield spread and one can see from the picture 7 that residuals are positively autocorrelated. The histograms for CCI and PMI are shown in Appendix 15.



Picture 7. *Histogram of the classical linear regression residuals for Yield Spread*

This means that our significance test could be misleading, since the standard error is not calculated in the presence of autocorrelation and with the yield spread also the heteroscedasticity. Fortunately this can be rather easily to be dealt with by applying Newey-West technique.

4.3.1 Dealing with Heteroscedasticity and Autocorrelation

The heteroscedasticity and autocorrelation in our linear model raises the issue that normal way of calculating the standard errors does not apply anymore. Since the standard error affect the calculations of the significance tests we need to adjust its calculation in presence of heteroscedasticity and/or autocorrelation. This is done by applying the technique introduced by Newey and West (1987). We used statistical software (WinRats) to calculate the new standard errors and ultimately the statistical significance levels. The results for the macroeconomic indicators with the Newey-West method are shown in table 9.

Table 9. Linear Regression with Newey-West correction

Regression	I	II	III
Intercepts	0.01277 2.10	0.02712 12.38	-0.03113 -1.50
Yield Spread	0.79561 3.14	-	-
CCI	-	0.06096 2.70	-
PMI	-	-	0.00112 2.90
Num. Of Obs.	104	104	104
Adj. R-Square	0.1163	0.0803	0.0428
F-Stat	14.68	10.80	5.65

Model $\Delta GDP_t = \alpha + \beta(Variable_{t-k}) + u_t$, with quarterly data and corrections to the significance level calculations with Newey-West technique. First row shows the intercepts (α) of the linear model for each regression. After that there is shown the coefficients (β) for each variable respectively. The t-statistics are shown in second in each row. All of the variables were lagged with the value of k as follows: $Yield\ Spread_{t-6}, CCI_{t-1}, PMI_{t-1}$. Yield Spread = Difference between Market yield on 10-year U.S. Government bonds and the Market yield on 3-month securities. PMI = Purchasing Managers Index. CCI = Consumer Confidence Index.

After the correction to the standard error, yield spread's t-value is a bit lower but still significant, since it is over 2, same thing with the intercept of the test. The regression model with yield spread as an explanatory variable is statistically significant. With the CCI the test is also statistically significant, after the correction to the standard error, and the test is statistically significant. When testing the PMI, with the Newey-West estimation, coefficient stays statistically significant, but the intercept does not statistically differ from 0.

We also tested how the R-square changed after adjusting the model to the serial correlation problem. This was done in SAS Enterprise Guide 4, with the linear regression in presence of autoregressive errors. The method used was the maximum likelihood method. The results for this are presented below in table 10.

Table 10. Parameter Estimates of the Maximum Likelihood method

Regression	I	II	III
Intercepts	0.01277 2.10	0.02712 8.6	-0.03113 -1.25
AR1	-0.3686 -4.01	-0.4032 -4.30	-0.4101 -4.31
Yield Spread	0.7347 2.65	-	-
CCI	-	0.0245 1.39	-
PMI	-	-	0.0007 1.11
Num. Of Obs.	104	104	104
Adj. R-Square	0.2453	0.2134	0.2086

Maximum likelihood estimates with quarterly data. First two rows show the intercepts (α) and the AR1 procedure of the Maximum likelihood model for each regression. After that there is shown the coefficients (β) for each variable respectively. The t-statistics are shown in second in each row. All of the variables were lagged with the value of k as follows: $Yield\ Spread_{t-6}, CCI_{t-1}, PMI_{t-1}$. *Yield Spread = Difference between Market yield on 10-year U.S. Government bonds and the Market yield on 3-month securities. PMI = Purchasing Managers Index. CCI = Consumer Confidence Index.*

This was done to find out how would the estimate change and more importantly to see how the explanatory power of the indicators changed. We can see from table 10, that linear regression with autoregressive errors is also statistically significant with the yield spread, but not with the CCI or PMI.

This method gave a higher total R-square for yield spread than OLS. The R-square calculated with the maximum likelihood method for yield spread was 0.2453 or 24.5 %, almost a double, compared to the OLS R-square. When considering the Maximum Likelihood method for CCI and PMI, we can see from table 10 that coefficients do not statistically differ from 0.

4.4 Linear Regression with multiple variables

We wanted also to test how our models R-square would improve if we added more explanatory variables and see if the R-square would improve when explaining the changes with more than just one variable. We also wanted to see if there were econometric basis to combine the indicators signals, when considering their use as a base for investment strategy.

Table 11. Parameter Estimates of the Multiple Linear Regression

Intercept	Yield Spread	CCI	PMI
0.00307	0.65075	0.04390	0.00024
0.12	3.00	2.18	0.48
[0.15]	[2.54]	[2.10]	[0.57]
Num. Of Obs.	104		
Adj. R-Square	0.1530		
F-Stat	7.26		

Model $\Delta GDP_t = \alpha + \beta_1 \beta X_{1t-k} + \beta_2 \beta X_{2t-k} \beta_3 \beta X_{3t-k} + u_t$, *with quarterly data. Table shows the intercept (α) t-statistics and Newey-West corrected t-statistics of the linear model respectively, next three columns shows the coefficient (β,) t-statistics and Newey-West corrected t-statistics respectively. All of the variables were lagged with the value of k as follows:* $Yield\ Spread_{t-6}, CCI_{t-1}, PMI_{t-1}$.*Yield Spread = Difference between Market yield on 10-year U.S. Government bonds and the Market yield on 3-month securities. PMI = Purchasing Managers Index. CCI = Consumer Confidence Index.*

As one can see from the table 11; Changes in Purchasing Managers Index does not give statistically significant results and the intercept of the test does not differ from 0 either. Yield spread and CCI are statistically significant in multiple linear regression. The adjusted R-square for multiple linear regression was 15.30 %. All of the variables were lagged, but we lagged the CCI and PMI by only one quarter, since they do not lead GDP as much as yield spread. Yield spread was lagged 6 quarters; these were the same as with the Classical Linear Regression, when testing the variables by themselves. As one can see from table 11, the PMI is not anymore statistically significant even thought by itself the PMI was statistically significant variable. This probably derives from cross correlation between the explanatory variables. We constructed a correlation matrix between the values of the explanatory variables, which are presented in table 12.

Table 12. Correlation between the Macroeconomic indicators

	Yield Spread	PMI	CCI
Yield Spread	1.0	0.1643	0.1131
PMI	0.1643	1.0	0.3871
CCI	0.1131	0.3871	1.0

Cross Correlation between the explanatory macroeconomic variables used in linear regression and multiple linear regression. Yield Spread = Difference between Market yield on 10-year U.S. Government bonds and the Market yield on 3-month securities. PMI = Purchasing Managers Index. CCI = Consumer Confidence Index.

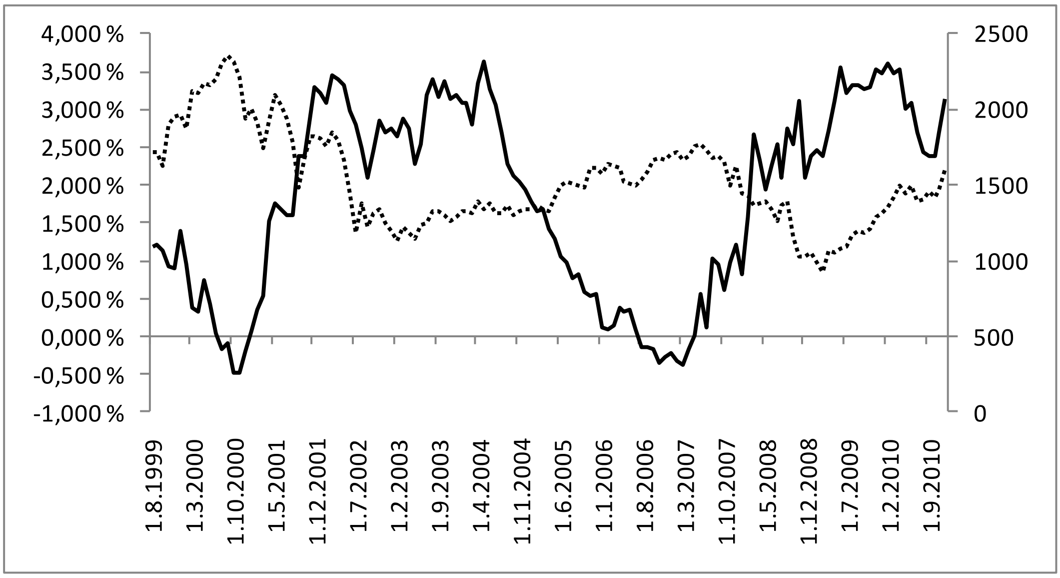
As we can see from table 12 PMI correlates quite strongly with other explanatory variables, especially with CCI.

4.5 Signal values of the Macroeconomic indicators

The lead relationship between the macroeconomic indicators and the stock market is an important thing to study, so that the indicators that tells us where are we in the economic cycle can be applied as a basis of a hedging strategy. In above we examined that indicators had been able to predict the changes in terms of the GDP development in last 26 years and that relationship was statistically significant, but the stock market is also an indicator of a real economy and it reacts to the possibility of a recession and it is a leading indicator for the real economy. As mentioned in chapter 2.7 several previous studies have examined this relationship. As Chen (1991) concluded the macroeconomic indicators ability to predict the growth in the economy relates to its ability to forecast market returns. This is the reason we examined with regression analysis the explanatory power of the macroeconomic variables in selected time period. This is why wanted to construct an exercise that examines the macroeconomic indicators performance to lead the stock market. This was done to see, if the indicator was signaling the recession or an economic downturn before the stock market did, or is the indicator indicating the downturn because the stock market indicated it first.

4.5.1 Yield Spread

As mentioned above in related literature, theoretical background and in our in-sample regression, yield spread is able to explain the growth of total GDP and it is able to give warning signals about future recession in real economy and these results have been statistically significant. In addition to this in theoretical background we showed that academic literature has been able to prove the relationship between macroeconomic indicators and stock market returns, (see e.g. Chen 1991). The question becomes does the yield spread signal recession in time, so it is useful considering hedging in stock portfolios, or stock indices?



—= *Yield Spread* *- - - = S&P 500 Index*

Picture 8*. Comparison of the Yield Spread and S&P 500 monthly total return index development from 1999 to 2010. The spread showed is the difference between Market yield on 10-year U.S. Government bonds and the Market yield on 3-month securities. Left y-axel is the spread in % and right y-axel is the level of S&P 500 index.*

In picture 8 is shown the comparison of the yield spread and the S&P 500 index. In the last 10 years the yield curve inverted twice and the stock market faced two major crises, in 2001 and in 2008. From picture 8 one can see that the yield spread has clearly been leading the S&P 500 index in last decade. In both recessions and stock market crashes, the spread had inverted before the stock market begun to react to the threat of the coming recession.

A numerical analysis, from the data that was used to draw picture 8, shows that in terms of total monthly returns the S&P 500 has had 19 months in last 10 years, were the total monthly return was over 5 % negative (which translates to 79 % negative annualized total return). In 18 of them the yield curve had inverted before they appeared. Naturally some of the negative months appeared a considerably long time after the spread had gone negative, but most of them appeared within 18 months after the inversion and some right after it. Only once the S&P 500 index had over 5% negative total return in one month, before the spread had inverted, and before that the spread had already flattened a lot. This analysis seems to tell the same story as picture 8. Yield spread has reacted before the S&P 500 index and not the other way around.

We used certain filters to come up with the rule, when the signal that yield spread is giving can be considered as true and when it is false. First we needed to come up a time frame. In this context we came up with 1 year time frame. In row marked "*" we determined that the spread had signaled correctly if the S&P 500 index annualized monthly return was over 100 % negative (5.95 % a month) in at least one of the following 12 months after the yield spread had inverted. In row marked "**" the rule was that signal was correct if the S&P 500 index annualized monthly return was over 100 % negative in at least two of the following 12 months after the yield spread had inverted. The data used was monthly data, from the years 1999-2010, in which time the yield spread turned negative twice, and was negative in 14 different months. The signal was considered when the spread inverted more than 3 months in a row, in other words the yield spread needed to be negative at least one quarter, or it was not considered to be a signal. During the period the spread was inverted every time over one quarter, first in August 2000 to December 2000 (5 months) and the other time in August 2006 to April 2007 (9 months).

Table 13. Signal Value of the Yield Spread

	*	**
True Signals	11	9
False Signals	3	5
Total Signals	14	14
Accuracy rate	79 %	64 %

** S&P 500 index's Annualized total monthly return over 100 % negative in one of the following 12 months after the Yield Spread inverts*

*** S&P 500 index's Annualized total monthly return over 100 % negative in two of the following 12 months after the Yield Spread inverts*

As we can see from the table 13, the results of this exercise tell the same story as the theory considering yield spread. Most of the big negative monthly returns occurred about 8-12 months after the signal of a recession. In this sense the 12 month filter rule seems to be appropriate. We also took a look of all the big negative monthly returns and during our time period all the big negative monthly returns (over 8 % declining in a month) occurred after the yield spread had inverted. When filtering this with simple time rule, 55 % of the dramatic negative monthly returns occurred within 12 months after the spread inverted and all of the big negative months occurred within 24 months after the negative spread period. In this time period (1999-2010) there were two major crises in the stock market. In both times the yield spread was able to give a hint of the hard times coming and in a monthly basis the hard times in the stock market seemed to come in two different waves. First about 8-12 months after the yield spread had been negative and the second wave of the crash seemed to come within 20-24 months after the spread had inverted and the returns seemed to be more negative than in the first wave. This may be due the fact that, first the stock market is indicating the same total economy recession as the yield spread, but spread is doing that sooner. Then the recession actually hits and there is no question about it anymore and stock market reacts again, but this time even more dramatically.

4.5.2 Purchasing Managers Index

As mentioned in theoretical background the PMI readings over 42.7 are interpreted as signals that the overall economy is expanding, hence we applied this and made a rule that a reading below 42.7 signals possible recession in the economy. This was then applied to the stock market and tested how well the PMI index alone would have helped to warn about the crash. We used the same data set as we used with the yield spread and we used the same rules to determine if the signal was true or false. Presented in table 14, the PMI index gave more false than true signals. Actually it seemed that the S&P 500 index took a turn before the PMI readings were able to catch up. In this light it seems that over the last 10 years the S&P 500 index was leading the PMI.

Table 14. Signal Value of the Purchasing Managers Index

	*
True Signals	5
False Signals	7
Total Signals	12
Accuracy rate	42 %

** S&P 500 Index's Annualized total monthly return over 100 % negative in at least one of the following 12 months after the PMI index is below 42.7*

We took a closer look to this and found out that S&P 500 index monthly returns were leading the PMI index. The PMI index seemed to take a big hit right after the stock market had crashed in the previous month.

4.5.3 Consumer Confidence Index

With the Consumer Confidence Index, we applied a rule where CCI was interpreted signaling recession if the change was -5 % or more in two months in a row. We applied this rule and examined how Consumer Confidence Index had signaled recession in overall economy and if it signaled those in time to gave warning about crashes which were on the way in the stock market, during our investing period (1999-2010). In table 15, there is showed the signals and accuracy during period mentioned before.

Table 15. Signal Value of the Consumer Confidence Index

	*
True Signals	5
False Signals	2
Total Signals	7
Accuracy rate	71 %

** S&P 500 Annualized Total monthly return over 100 % negative in at least one of the following 12 months after the applied CCI signals are signaling recession.*

Even though the accuracy rate is over 70 %, we need to point out some falls with the signal value. First of all we can see that the number of total signals which this indicator gave for the investment period is only half of the signals which yield spread gave. This is because the S&P 500 index seemed to lead the Consumer Confidence Index, and 6 of the 7 times (almost 87 % of the total signals) CCI gave a signal only few months after the S&P 500 had annualized monthly return over 100 % negative. This explains the number of total signals. It seems that, at least in our investment period, S&P 500 index is a reason for the declining consumer confidence. The first drop in stock markets affects the consumer confidence. So it seems that S&P 500 index is indicating recession before Consumer Confidence Index and actually affects consumers' expectations. If the threat of a recession realizes, the stock market reacts again and consumer confidence has made a signal for that reaction, since it is reacting to the first drop in stock markets. In all of the cases that CCI signaled correctly, stock market was declined dramatically just few months before.

To summarize all of the macroeconomic indicators turning point signals in the context of our filter rules we constructed the following table. In table 16 you can see how well has these signals worked in the context of signaling at least one major crash in the following year after the indicator signaled a recession. Table 16 does not explain the lead relationship between the indicator and S&P 500 index.

Table 16. Summary of the Signal Values

	Accuracy rate	Total signals
Yield Spread	79 %	14
PMI	42 %	12
CCI	71 %	7

Yield Spread = Difference between Market yield on 10-year U.S. Government bonds and the Market yield on 3-month securities. PMI = Purchasing Managers Index. CCI = Consumer Confidence Index. Table above provides a numerical analysis how accurately indicators would have worked in signaling at least one major crash in the S&P 500 index in the following year after the indicator signaled a recession in the U.S. economy These figures does not explain the lead relationship between the indicator and S&P 500 index.

4.6 The Examination of different Strategies

The examination and comparison was executed by back testing the strategies performance. In order to do this we needed to examine the indicators and see when they were signaling negative future for the stock market. In both, macroeconomic and technical analysis based strategies; timing of the hedge was naturally crucial thing for the strategy to generate profits. We wanted the back testing to be real simulation of the investments done as the applied indicators signals. This practical example of using the indicators can be seen as an out-of-sample prediction for our macroeconomic indicators, in terms of avoiding the downside risk of the stock markets.

We needed to decide how long the hedge would continue after the indicator signaled a crash ahead. All the other indicators, besides yield spread, have an ending point for the signal. With CCI and PMI the turning point is same in negative and positive turn. Technical analysis indicators have clear turning points when to stop the hedge; when trading rule says that it is time to buy, the hedging is naturally discontinued. The signals for hedge and the timing issues are discussed more in the results part of each indicator.

4.7 Macroeconomic Indicators based Hedging Strategies

4.7.1 Yield Spread

As stated before, yield spread does not provide clear signal for to hedging to be stopped. Timing issues are difficult and not obvious for this indicator.

Although the yield spread has been historically been very effective in anticipating and estimating recessions and this relation has been proven in several academic studies, the time of the lag is not constant. Further, in this study we are trying to predict stock market returns and crashes, which naturally are in relation with the overall economy, but this generates more difficulties when considering when to start and stop the hedge.

This is why we wanted to do a somewhat systematic timing for the yield spread based hedge. We started the hedge after the spread had gone negative and continued it for 12 months ahead. So starting point was first negative signal and hedging stopped after the 12 months after the last negative signal. In our research period (8/1999 – 12/2010) we had two crashes and yield spread was able to signal them both. The returns however were closely in relation with the timing. We constructed also another yield spread based hedging strategy were the rolling time ahead was 18 months. This is in line with the in sample estimation were the lag employed was 6 quarters (18 months). The results for both of these yield spread based hedging strategies are presented in table 17.

Table 17. Results for Yield Spread based Hedging Strategies

	Yield Spread 1	**Yield Spread 2**
Total profit from options	283 361	781 799
Total number of options bought	37	49
Number of options that had value on maturity	16	25
Success rate	43.24%	51.02%

Table explains the results from option positions acqruided on base of the indicator signals. Table 17 presents option position results for two strategies, both based on the yield spread signals of real economy recession.

We can see from table 17, that both of the yield spread based strategies would have been profitable. Clearly the 18 month ahead hedged strategy would have been more profitable and also signaling more correct hedges. This is a great example how the timing is crucial, as it naturally always is. The longer hedge has naturally more options in it, but it is performing significantly better.

Form this we can conclude that yield spread has been affective indicator in the last 10 years when signaling recessions and stock market crashes.

Negative spread would definitely work as s warning system for an investor. On the other hand yield spread alone does not tell when to start or stop the hedging and optimum would be to follow more closely other indicators after the spread is signaling rough times for the economy in the near future. The strategy based on yield spread, needs another indicator to tell when the economy is taking the upward trend, and ultimately, when the turbulence in the stock market is over. More on this can be found in chapter 4.9.2.

4.7.2 Purchasing Managers Index

With the PMI and actually the rest of the indicators, the problem mentioned with the yield spread considering timing was no longer an issue. With PMI we used the same rule as before to interpret the turning point in the economy and in stock markets. This meant that when the PMI went below 42.7 it was considered as a signal to hedge and when it went above 42.7 the hedging was discontinued. The limit derives from a general interpretation of the indicator (Koenig 2002). The hedging results for PMI based strategy are presented in table 18.

Table 18. Results for PMI based Hedging Strategy

	PMI
Total profit from options	-99 776
Total number of options bought	12
Number of options that had value on maturity	6
Success rate	50.00%

Table explains the results from option positions acqruided on base of the indicator signals. Table 18 presents option postion results for a strategy based on PMI´s (Purchasing Managers Index) signals of real economy recession.

All the numbers in table 18 tells the same crushing story for PMI based hedging strategy. The profit form options bought is negative, so hedging actually caused a negative impact for the portfolio. There were not as many months that signaled hedging as other indicators and those which were signaling a downhill in the economic cycle, every other had negative total value.

4.7.3 Consumer Confidence Index

When researching consumers' confidence in terms of signaling market turning points we used the same signal rules as in chapter 4.5.3. When the CCI was at least 5 % negative in two months in a row, it was interpreted as a signal to hedge. The hedge was continued as rolling bases as long as the CCI gave a signal that economy is facing a turning point. This was when CCI was at least 5 % positive in two months in a row. The results for CCI based hedging strategy are presented in table 19.

Table 19. Results for CCI based Hedging Strategy

	CCI
Total profit from options	350 136
Total number of options bought	48
Number of options that had value on maturity	22
Success rate	45.83%

Table explains the results from option positions acqruided on base of the indicator signals. Table 19 presents option postion results for a strategy based on the CCI's (Consumer Confidence Index) signals of real economy recession.

From table 19 we can see that CCI performed quite well in terms of profit from options. It actually had more options which had negative impact for the portfolio, but the options which had value covered those and clearly applied CCI signals were able to predict big crashes in the selected time period and this way hedging was effective.

4.7.4 Macroeconomic Indicators Combined

In addition to the examination of the macroeconomic indicators as individuals we constructed a strategy were investor took all of the three indicators and made the hedging decisions based on all of the indicators. First we examined a strategy were all three indicators were combined and if one of them were signaling recession hedging was employed. The other combination we examined was a combination of the yield spread and Consumer Confidence Index. In this strategy the hedge was started when either of the indicators signaled recession and stopped when applied CCI signals showed a positive turn in the economy. The results for both of these strategies are presented in table 20.

Table 20. Results for Combined Macroeconomic Indicators based Hedging Strategy

	Combined Macroeconomic indicators	Yield Spread and CCI Combined
Total profit from options	337 130	551 274
Total number of options bought	74	62
Number of options that had value on maturity	33	29
Success rate	44.59%	46.77 %

Table explains the results from option positions acqruided on base of the indicator signals. Table 20 presents option position results for two strategies: First is based on all of the macroeconomicindicators used in this study (Yield Spread, Purchasing Managers Index and Consumer Confidence Index) signals of real economy recession. The second strategy presented in the table is based on the combination of signals of recession given by yield spread and Consumer Confidence Index.

From table 20 we can see that when combining all of the signals, the strategy has been profitable and hedging with put options has worked. Although more than half of the options had negative impact in a portfolio as a whole the indicators and the hedging strategy was able to predict major negative stock return months and that way it was able to have profit.

We also constructed a strategy where investor would use yield spread and CCI. This reflects the multiple linear regression estimation done before. Both of these indicators were able to give statistically significant results when explaining together the GDP development. Yield spread was also able to lead the S&P 500 index downturn in the investment period. CCI is able to explain the GDP, so it is justifiable to use it as another indicator to find out when the storm has passed. In this strategy the hedging was started after the yield spread inverted and stopped when CCI signaled that turn for the better was about to come. As we can see from table 20, this kind of combination, was able to made profit from option positions in our selected investment period.

4.8 Technical Analysis based Hedging Strategies

In technical analysis we needed to use the trading rules in terms of the hedging strategies. Whenever an indicator showed a sell signal and bearish market trend, hedging was applied. We used monthly data in our examination, but technical analysis is often more used in day or week trading. This is why we employed a strategy were the signals were constructed in daily and weekly basis but the options were bought once a month. If the indicator did not signaled turning point before and close to acquirement of an option, the option was not bought or if did, the hedging was continued.

4.8.1 Moving average

The moving average was constructed with the 1-200 rule, where the short moving average is simply the level of index of each day. The long leg was 200 day moving average of the index. In moving average a sell signal is generated when the short-term falls below the long-term moving average. We employed this rule and adjusted it that when the sell signal was generated the hedge was employed, in other words put option was bought. This was done as long as the short-term was below the long-term and after it had crossed and the simple MA showed a buying signal the hedging was stopped.

Table 21. Results for Moving average based Hedging Strategy

	Moving Average
Total profit from options	373 222
Total number of options bought	70
Number of options that had value on maturity	30
Success rate	42.86%

Table explains the results from option positions acqruided on base of the indicator signals. Table 21 presents a strategy based on tehcnical indicator MA's (Moving Average) 1-200 rule signals of stock market trend.

As we can see from table 21 simple MA based strategy was able to hedge some of the downhill and made profit with options. We can also see that it gave a much more signals to hedge than any of the macroeconomic indicators based strategies. It had more signals that did actually give a negative impact, but it was able to hedge the months, which had big negative returns, hence the total profit was positive. In our research period there were two big crashes and predicting the big losses in them carried a long way for moving average, in terms of profit.

4.8.2 Moving Average Convergence-Divergence

In construction of the hedging strategy based on MACD (Moving Average Convergence-Divergence) we used weekly data and the most popular

MACD form 12/26, where the short EMA is 12 weeks and long EMA is 26 weeks. The signal line was the 9 week long EMA of the 12/26 MACD. The signals for hedging were derived from the MACD trading rules and bearish market trends were predicted when MACD readings were falling towards zero or were negative. When this was the case near the option acquiring the hedging was started and continued as long as MACD showed bearish trend. Trend was considered over when MACD readings were turning up; crossing to above the signal line.

Table 22. Results for MACD based Hedging Strategy

	MACD
Total profit from options	219 546
Total number of options bought	55
Number of options that had value on maturity	20
Success rate	36.36%

Table explains the results from option positions acqruided on base of the indicator signals. Table 22 presents a strategy based on tehcnical indicator MACD's (Moving Average Convergence-Divergence) signals of stock market trend. The form of MACD used was 12/26 and signal line was 9 periods long.

We can see form table 22 that strategy based on MACD was profitable, although success rate for signals was not impressing. Only 20 of the 55 options were able to make profit.

4.8.3 Relative Strength Index

The third technical indicator we used to predict market turning points was Relative Strength Index or RSI. Again the use of this technical indicator needed shorter data to construct the indicator data which was then interpreted. We used daily data and 14-day time period to construct the relative strength of the S&P 500 index for each day of the research period. With the RSI the significant turning points can be observed from the middle line (see picture 6, from chapter 2.3.3). RSI readings above 50 are interpreted to indicate that the market is bullish and readings below 50 are interpreted to indicate that the market is bearish, so the middle line (50) becomes the line for the start of the hedge and naturally also the stop. We had daily data, but our options that we could use in this study, due to a reason of data issues, had a maturity of 1 month. We needed to observe the RSI before the option acquiring date and see what did the indicator showed around that time. Hedging was started when RSI crossed the middle line from above and it was stopped when the RSI came back above the middle line. The results for RSI based hedging strategy are presented in table 23.

Table 23. Results for RSI based Hedging Strategy

	RSI
Total profit from options	421 779
Total number of options bought	74
Number of options that had value on maturity	33
Success rate	44.59%

Table explains the results from option positions acqruided on base of the indicator signals. Table 23 presents a strategy based on tehcnical indicator signals of 14-day RSI (Relative Strength Index) stock market trend.

As we can see from table 23, RSI was able to provide a strategy were options made profit. Although success rate was a under 50 %, clearly RSI was able to indicate the biggest negative returns in the selected investment period.

4.8.4 Technical Analysis Methods Combined

As we with the macroeconomic indicators we also did a combined strategy including all the technical indicators. This was constructed to have all the signals of the three technical indicators in the same strategy. As we can see from table 24 this strategy gave a lot of signals to hedge, but it was profitable under 50 % of the time. Nevertheless options bought according to this strategy made profit in total and strategy would have been able to ease the fall investor would have faced in the investment period. Results for combined strategy are presented in table 24.

Table 24. Results for Combined Technical Analysis based Hedging Strategy

	Combined Technical Analysis
Total profit from options	283 145
Total number of options bought	95
Number of options that had value on maturity	40
Success rate	42.11%

Table explains the results from option positions acqruided on base of the indicator signals. Table 24 presents a strategy, where the signals of stock market trend is based on all of the technical indicators used in this study (Moving Average (MA), Moving Average Convergence-Divergence (MACD) and Relative Strength Index (RSI).

4.9 Comparison of the Hedging Strategies

In introduction we listed the 4 research problems, which we were searching an answer for. In this chapter we are going to present an answer for questions considering comparison of the hedging strategies for the selected time period. This is only an example how an investor could have used the information about the upcoming recession and this is done to compare the signals to history based technical analysis. Furthermore this is to show that in chosen time period, investor would have been able to profit from the use of macroeconomic indicators, as well as technical analysis in terms of avoiding the downside risk in the stock markets.

The comparison of the strategies was executed by the comparison of the risk-return tradeoff of the strategies (Sharpe's ratio). As mentioned before in chapter 3.3.3, there are two components that make the difference in Sharpe's ratios: the profit and the volatility. In other words a strategy which was volatile should have more profits than a strategy that was not as risky. The use of put options naturally affected the profits and the volatilities of different strategies. In general the last decade was not a good one for the S&P 500 index and the Sharpe's ratios are considerably low in all of the strategies. However, this gives us a mean to compare the indicators in terms of the risk-return trade off, not just the pure profits from put options. We compared the total profit, volatility and Sharpe's ratios of the strategies.

4.9.1 Buy-and-Hold Strategy

Table 25 presents the results for buy-and-hold strategy. In this there were no options used and as the name of the strategy implies; the fictive index portfolio was bought in the beginning of the investment period and hold to the end of it. This gives us a comparison point and answers the question, would the hedging with put options based on different indicators been able to provide the much needed hedge.

Table 25. Comparative Results for Buy-and-Hold Strategy

	Buy and Hold
Value of the portfolio at the end of 2010	933 676
Value of the portfolio at 8/1999	1 000 000
Profit	-66 324
% -profit	-6.63 %
Annualized Volatility	21.30 %
Sharpe Ratio	-0.148
Investment time in years	10.33
Annualized profits	-0.66 %

buy-and-hold strategy: the investor does not sell or hedge ones portfolio. In this case represents the development and profits of S&P 500 total return index for the last decade.

4.9.2 Macroeconomic Indicators based Strategies

The results for macroeconomic strategies are presented in tables 26, 27 and 28. As we can see from table 26, the yield spread based strategy was successful. However, the strategy where hedging was rolled 12 months ahead was outperformed by the 18 month one. This points out how important the timing is. Unfortunately we cannot know when to stop the hedge with just using the yield spread.

Table 26. Comparative Results for Yield Spread

	Yield Spread 1	Yield Spread 2
Value of the portfolio at the end of 2010	1 218 900	1 718 811
Value of the portfolio at 8/1999	1 000 000	1 000 000
Profit	218 900	718 811
% -profit	21.89 %	71.88 %
Annualized Volatility	26.89 %	29.88 %
Sharpe Ratio	-0.021	0.097
Investment time in years	10.33	10.33
Annualized profits	1.93 %	5.38 %

Yield spread 1: A hedging strategy where hedging was started next month after the yield inverted and rolled on for next 12 months. Yield Spread 2: Same as before, but hedging was rolled for 18 months. Yield Spread = Difference between Market yield on 10-year U.S. Government bonds and the Market yield on 3-month securities.

Sharpe's ratio was negative for yield spread 1 but it was able to outperform the buy-and-hold strategy. Yield Spread 2 gave the best results of the strategies.

Table 27 shows the comparative results for CCI and PMI. As one can see the CCI based strategy was effective one and hedging made according to the signals of CCI about the GDP development would have paid off.

Sharpe's ratio is close to zero. Even thought the S&P 500 index seems to lead the CCI, the applied CCI signals were able to spot the most dramatic changes in the S&P 500 index. These results are in line with the signal values studied in chapter 4.5. With PMI based hedging the investor would have made the wrong bets and the hedging according to PMI was late. This reflects the signal values that PMI had and derives from the fact that S&P 500 index is leading the PMI and not other way around. Sharpe's ratio for PMI is the worst of all hedging strategies.

Table 27. Comparative Results for CCI and PMI

	CCI	**PMI**
Value of the portfolio at the end of 2010	1 286 608	834 665
Value of the portfolio at 8/1999	1 000 000	1 000 000
Profit	286 608	-165 335
% -profit	28.66 %	-16,53 %
Annualized Volatility	31.37 %	25.18 %
Sharpe Ratio	-0.001	-0.168
Investment time in years	10.33	10.33
Annualized profits	2.47 %	-1.73 %

In both; Consumer Confidence Index (CCI) and Purchasing Managers Index (PMI) abased hedging strategies options where acquired after the indicator was signaling a downturn in the overall economy. Hedging was rolled on as long as the indicator did not signal the upward trend in overall economy.

When using all three macroeconomic indicators the strategy is successful in terms of the profit. Sharpe's ratio is close to zero. This strategy is a bit more volatile than strategies with only one macroeconomic indicator.

When combining the yield spread signals about the recession and CCI signals about the change in GDP development, we can access to a strategy where yield spread signals that something fuzzy is about to happen in real economy which would have a negative impact in the stock markets. CCI role in this is to signal that the storm is about to be over and upward trend is coming back to the real economy and hedging in the stock market can be stopped.

This kind of strategy allows us to base the stop of the hedge which was based on inversion of the yield spread. The results of multiple linear regression supports this discussion, since yield spread and CCI were statistically significant variables in in-sample-estimation of the GDP changes. The combined strategy based on both of these indicators (yield spread and CCI) would have worked and actually gave second best results of all of the strategies in chosen investment period. Only the 18 months ahead rolled yield spread was able to outperform it. The fact that CCI was not able to predict the downturn in September 2008 and that the hedging was stopped before it had a lot to do with this. The yield spread and CCI based strategy was also a bit more volatile than strategies which used only one indicator. Table 28 provides the results for combined macroeconomic strategy and for combination of yield spread and CCI.

Table 28. Comparative Results for Combined Macroeconomic indicators and Yield Spread & CCI based Strategy

	Combined ME	**Yield Spread & CCI**
Value of the portfolio at the end of 2010	1 242 675	1 484 951
Value of the portfolio at 8/1999	1 000 000	1 000 000
Profit	242 675	484 951
% -profit	24.27 %	48.50 %
Annualized Volatility	34.76 %	32.04 %
Sharpe Ratio	-0.011	0.044
Investment time in years	10.33	10.33
Annualized profits	2.12 %	3.90 %

Combined macroeconomic Indicators: A hedging Strategy, where the option acquiring was executed according of all three macroeconomic indicators (Yield Spread, Purchasing Managers Index and Consumer Confidence Index). Hedging was started when ever one of the indicators signaled downturn in the economy. Yield Spread and CCI (Consumer Confidence Index): A strategy where hedging was started when yield spread inverted and rolled on until the CCI signaled that downturn was about to be over and upward trend was coming.

4.9.3 Technical Analysis based Strategies

Table 29 presents the technical indicators on their own. As we can see, volatility is higher than with the macroeconomic indicators. MACD gave the worst results of the technical indicators and its Sharpe’s ratio was also negative. Moving average and RSI got pretty good results in terms of profit, but Sharpe’s ratios were close to zero. When comparing to the macroeconomic indicators, by own the technical indicators seemed to perform better than CCI or PMI alone, but when comparing to the yield spread & CCI combination, none of the technical indicators was able to outperform it.

Table 29. Comparative Results for Technical Analysis Indicators

	MA	MACD	RSI
Value of the portfolio at the end of 2010	1 310 931	1 156 198	1 359 479
Value of the portfolio at 8/1999	1 000 000	1 000 000	1 000 000
Profit	310 931	156 198	359 479
% -profit	31.09 %	16 %	36 %
Annualized Volatility	35.92 %	36 %	34 %
Sharpe Ratio	0.005	-0.030	0.015
Investment time in years	10.33	10.33	10.33
Annualized profits	2.65 %	1.41 %	3.02 %

MA: Moving average based strategy where hedging was started when MA showed sell signals and rolled on as long as the market trend was bearish according to the Technical indicator. The same kind of strategy was applied also with Moving Average Convergence-Divergence (MACD) and Relative Strength Index (RSI) based hedging strategies.

Table 30 presents the comparative results for a hedging strategy that combines all three technical analysis methods. We can see that this strategy had the biggest volatility. Even though the strategy was able to ease the downturn its Sharpe’s ratio is almost as low as with the buy-and-hold strategy.

Table 30. Comparative Results for Technical Analysis Indicators Combined

	Combined TA
Value of the portfolio at the end of 2010	1 221 709
Value of the portfolio at 8/1999	1 000 000
Profit	221 709
% -profit	22.17 %
Annualized Volatility	37.43 %
Sharpe Ratio	-0.014
Investment time in years	10.33
Annualized profits	1.96 %

Combined Technical Analysis Indicators based strategy where hedging was started when any of the technical indicators (Moving Average (MA), Moving Average Convergence-Divergence (MACD) or Relative Strength Index (RSI)) showed sell signals and rolled on as long as the market trend was bearish according to any of the technical indicators.

5 SUMMARY AND CONCLUSIONS

The purpose of this study was to examine macroeconomic indicators' and technical analysis' ability to anticipate market crashes. We wanted to find out if commonly used macroeconomic indicators, used to signal and predict future GDP changes, can be used as a warning system for stock market crashes. The hypothesis is that the signals of a recession can be used as signals of stock market crash and that way a basis for a hedging strategy. First we needed to examine how commonly followed macroeconomic indicators have been able to explain future GDP development in the U.S. in the most recent decades and recessions. Indicators we examined were the spread between 10 year and 3 month interest rate (Yield Spread), The Purchasing Managers Index (PMI) and the Consumer Confidence Index (CCI). The second research question was whether the commonly followed macroeconomic indicators were reacting in time, so that investors can use the information about recession to hedge against the downside risk at the stock market and how well these hedging strategies based on signals of recession would have worked in as a basis of actual hedging strategy performed with put options. We also wanted to compare macroeconomic indicators with some of the most popular technical indicators, like moving average (MA), Moving Average Convergence-Divergence (MACD) and Relative Strength Index (RSI), and with the buy-and-hold strategy.

The examination of future GDP development explaining ability of the macroeconomic indicators was performed with in-sample estimation of last 26 years. We concentrated only to the in-sample estimation, since the goal was to find out how well these indicators have been able to explain the changes and not to examine the accuracy of future GDP forecasts. All of the indicators were lagged by certain amount of time. When examining if the macroeconomic indicators have been reacting in time, we examined the total monthly returns of S&P 500 index and indicators levels, to conclude if the indicator had signaled recession in real economy in selected time period before S&P 500 index reacted to this fear. The performance of the indicators to work as a basis of a hedging strategy was examined in a practical example from the last decade. The hedge was applied when indicator showed a signal for a recession, or when technical indicator showed a bearish market trend in the stock market. When examining which indicator was able to provide the best hedging strategy, we constructed a comparison between different hedging strategies. The only difference between these strategies was the starting time and the stopping time of the hedge, in other words the indicators ability to signal stock market crashes in time. The profit for the portfolio was calculated as a combination of the index portfolio and option portfolio. From this total portfolio we calculated different evaluation measures like, Sharpe's ratio, volatility and annualized profit. We compared these measures among the strategies to find out if fundamental analysis, based on macroeconomic data was able to outperform a price history based technical analysis and buy-and-hold strategy in selected time period.

When performing a simple one explanatory variable linear regression all of the indicators gave statistically significant results and all of them had explanatory power over the future GDP development, so we can say that chosen macroeconomic indicators have contained information about the development of the GDP and recessions. However, when performing a multiple linear regression, where all of the indicators where explaining the changes in GDP in the same linear regression, the PMI was not anymore statistically significant. This derived from the cross correlation between the CCI and PMI. Yield Spread had the biggest explanatory power (R-Square) over the GDP development. In our research period the yield spread was the only indicator that gave signals about the recession, before the S&P 500 index reacted to the threat of a possible recession. However, the crash does not happen over a month and the CCI and, somewhat the PMI, can be used to analyze the state of overall economy. This means that these indicators can be used to determine when the storm is possible over and also to determine if the real economy is in a recession, before NBER announces it.

Problem with yield spread based hedging strategy from the investor's point of view is that one cannot know when to stop the hedge or how long it takes for the stock market to react to the threat of a recession after the inversion of the yield. This is why the most useful strategy is one that combines the fundamental analysis of the macroeconomics. We examined a hedging strategy which combined yield spread and Consumer Confidence Index. This hedging strategy gave second best results, after the 18 months ahead systematically rolled yield spread. In the past decade the yield spread, and ultimately the bond market has seemed to reacting to the possibility of a recession before the stock markets (see picture 8). This means that yield spread could have been used as a warning system for the stock market crash. Another conclusion can be made considering the comparison of the macroeconomic and technical indicators in the last decade. Macroeconomic indicators based hedging strategy that combined yield spread and CCI was able to give bigger returns than any of the technical analysis indicators or their combination, in the last 10 years. From this we can conclude that analysis of the S&P 500 index based on fundamental macroeconomic data was able to outperform the technical analysis in downside risk elimination strategy with put options in the chosen research period. Technical analysis performance was also useful and in chosen time period technical indicators based analysis of the stock market crashes was effective.

The put option data generated a limitation to our study. The data in hand consisted only at-the-money (ATM) put options' implied volatilities, from which we calculated the put option prices. This meant that we were only able to study hedging strategies where hedging was done with ATM put options. This meant that we could not "lock" the index level in previous month's level. Another limitation was also generated by the put option data. We only had 1 month maturity put options available, so we had to adjust the hedging accordingly. In real life, one could buy options of different maturities based on the signals that indicators give. In this example we only had the possibility to buy options which had maturity of

30 days, no longer or shorter. Third limitation relates also to the option data; we could not examine more risky investments, which would also had been based on the indicators signals, were investor would buy out-of-the money put options, when he or she is expecting a downturn in the markets. However, we were able to study how an equity investor could use macroeconomic indicators and the information they contain about the future state of the real economy. Adding to this, we established the lead relationship between the stock market and macroeconomic indicators in the last 2 recessions and stock market crashes. The results of this study can be useful for portfolio managers so they can add the weight of the hedging instruments in their portfolios or lower the weight of the stocks in aggregation funds based on the hedging signals.

The recession forecasting or examination how well indicators can predict the turn in the economy is not a new one. This relationship has been proven to exist in many studies before this. But this kind of research about macroeconomic indicators ability to provide effective warning signals for an equity investor in terms of possible stock market crashes has not been examined that widely. Furthermore this study examines how these signals would have worked in practice in the last decade, if used as a basis for hedging strategy. We also compared the performance of different indicators and technical analysis.

We used an indirect route with macroeconomic indicators to predict the stock market crashes. This indirect route derives from the relationship between recessions and market crashes (see chapter 2.1). The stock market is an indicator of a real economy and when investors are expecting the real output to decline in the future, they are demanding bigger rate of return, which leads to lower prices. Another way to see this is fear. Panic will take over and investors are selling their stocks and prices decline, bubbles bursts and water spills everywhere. Volatility in stock market goes to the roof and put option prices are raising. In this study we found that yield spread combined with applied Consumer Confidence Index signals of a recession has been most effective and most useful in signaling this relationship. The hedge was started after the yield spread inverted and continued as rolling hedge until the Consumer Confidence Index signaled a positive turn in the economy. The bond market seems to react to the fear of a recession before stock market and with Consumer Confidence Index we can have a clue when the storm is possibly over. Timing is naturally an issue in hedging and with these indicators one would have better clue when to start and stop the hedge.

Macroeconomic indicators have been judged to have a tendency to mislead the investors, but according to our research considering the last 10 years, the bond market (yield spread) has been able to signal the upcoming crash more effectively than technical indicators, like moving average. Generally the 12 month moving average is considered to be the best indicator of the stock market crashes in the U.S. but in this type of downside risk elimination the combination of yield spread and Consumer Confidence Index was able to outperform it. Yield spreads ability to work as a warning system depends on timing and we cannot assume it to be constant. For example the 18 month rolling hedge based on yield spread beat all the other strategies, but 12 month rolling hedge was not able to beat all technical indicators. This is why a combination of yield spread and some other indicator needs to be used. Based on this study, the best way to use the information that interest rate market clearly contains, is to combine the indicator to other macroeconomic indicators. However, there is no rule not to combine technical indicators and macroeconomic indicators and this study could be developed further to investigate different combinations of the fundamental macroeconomics and technical indicators to find out how to time the hedge more efficiently.

Inverted yield curve is not a normal state of the curve, and it tells that security investors are expecting or are afraid of the downturn in the economy. When consumers and investors are anticipating a turn in economic cycle, the U.S. government has ways of easing out the economy. With actions, including monetary and fiscal policy, they are stimulating the economy and the downturn is not as steep as it otherwise could be. Officials can use the macroeconomic indicators to know when to start the quantitative easing, before the recession actually occurs and that way generate steadier environment to the markets. Trust is everything and uncertainty about the future is poison to the markets. Quantitative easing programs can only go so far and politicians need to create a plausible economic policy so that measures of monetary and fiscal policy can work as they are intended and that the Federal Reserve’s role is not just to print more dollars and this way generating fears of hyperinflation to the markets and this way giving them more reasons to panic.

REFERENCES

Appel Gerald. "Become Your Own Technical Analyst: How to Identify Significant Market Turning Points Using the Moving Average Convergence Divergence Indicator or MACD " The Journal of Wealth Management, Vol. 6, No. 1. 2003: 27-36

Andrews Donald W.K ”Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimation." Econometrica, 59, 1991: 817 - 858.

Batchelor Roy, Dua Pami, “Improving macro-economic forecasts The role of consumer confidence” International Journal of Forecasting, 14, 1998: 71-81

Bodie Zvi, Kane Alex, Marcus Alan J. 2001. “Investments” 5th Edition The McGraw-Hill-Irwin, USA.

Brooks Chris, 2008 “Inroductory Econometrics for Finance”, 2nd Edition, Campridge University Press, UK.

Campbell, John Y. “Stock returns and the term structure” Journal of Financial Economics 18, no. 2, 1987: 373-399.

Chauvet Marcelle and Simon Potter. "Predicting a recession: evidence from the yield curve in the presence of structural breaks." *Economics Letters*, Volume 77, Issue 2, 2002: 245-253.

Chen, Nai-Fu, "Financial Investment Opportunities and the Macroeconomy" The Journal of Finance, Vol. XLVI, No.2, 1991:529-554

Chong Terence Tai-Leung and Ng Wing-Kam (2008). " Technical analysis and the London stock exchange: testing the MACD and RSI rules using the FT30", Applied Economics Letters, 15, 2008: 1111–1114

Consumer Confidence Survey® Technical Note, February 2011 [internet document], sited 7.3.2011, available at: http://www.conference-board.org/pdf_free/press/TechnicalPDF_4253_1311670800.pdf

Cox John C., Ingersoll Jonathan E. Jr. and Ross Stephen A., "An intertemporal general equilibrium model of asset prices", Econometrica 53, 1985: 363-384.

Dotsey, Michael "The Predictive Content of the Interest Rate Term Spread for Future Economic Growth", Federal Reserve Bank of Richmond *Economic Quarterly,* Volume 84/3, 1998: 31 - 51

Duarte Agustin, Ioannis A. Venetis and Ivan Paya. "Predicting total growth and the probability of recession." *International Journal of Forecasting*, 21, 2005: 261-277.

Estrella Arturo and Frederic S. Mishkin. "The predictive power of the term structure of interest rates in Europe and the United States: Implications for the European Central Bank." *European Economic Review*, 41, 1997: 1375-1401.

Estrella Arturo and Frederic S. Mishkin. "Predicting U.S. Recessions: Financial Variables as Leading Indicators." *The Review of Economics and Statistics*, Vol. 80, No. 1, 1998: 45-61.

Fama Eugene F. "The Behavior of Stock-Market Prices" The Journal of Business, Vol. 38, No. 1. 1965: 34-105

Fama Eugene F. "Stock Returns, Expected Returns, and Total Activity", The Journal of Finance, Vol. 45, No. 4 ,1990: 1089-1108

Fisher Kenneth L . and Statman Meir, "Consumer Confidence and Stock Returns", Vol. 30, The Journal of Portfolio Management, No. 1, 2003: 115-127

Hamilton James D. and Dong Heon Kim. "A Re-examination of the Predictability of Economic Activity Using the Yield Spread." *Journal of Money, Credit and Banking*, 34, 2002: 340-360.

Harvey, Campbell R. "The total term structure and consumption growth." *Journal of Financial Economics*, 22, 1988: 305-333.

Harvey, Campbell R. "Forecasts of Economic Growth form the Bond and Stock Markets." *Financial Analysts Journal*, septemper/october, 1989: 38-45.

Harvey, Campell R. "The Term Structure and World Economic Growth." *The Journal of Fixed Income*, Vol. 1 No.1, 1991: 7-19.

Holter, James T. 2009 " Using momentum analysis to predict price change",[internet document], sited 9.3.2011, available at: http://www.futuresmag.com/Issues/2009/October2009/Pages/Using-momentum-analysis-to-predict-price-change.aspx

Hull, John C. 2006, "Options, Futures and Other Derivatives" 6th edition. Prentice Hall Upper Saddle River, New Jersey.

Jansen Jos W. and Nahuis Niek J “The stock market and consumer confidence: European evidence”Economics Letters, Volume 79, Issue 1, 2003:89-98

Koenig, Evan F. "Using the Purchasing Managers Index to Assess the Economy’s Strength and the Likely Direction of Monetary Policy." *Federal Reserve Bank of Dallas Economic and Financial Policy Review*, Vol. 1 No.6, 2002: 1-14.

Mills, Terence C. "Technical analysis and the London Stock Exchange: Testing trading rules using the FT30", International Journal of Finance and Economics, 2, 1997: 319–331.

Moneta, Fabio. "Does the Yield Spread Predict Recessions in the Euro Area?." *International Finance,* Vol 8 No.2, 2005: 263-301.

Neftci Salih N. "Naıve trading rules in financial markets and Wiener-Kolmogorov prediction theory: A study of ‘technical analysis"The Journal of Business Volume 64, Issue 4, 1991; 549-571

Newey, Whitney K., and Kenneth D. West. "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent." *Econometrica, 55*, 1987: 703-708.

Newey, Whitney K., and Kenneth D. West. "Automatic Lag Selection in Covariance Matrix Estimation" Review of Economic Studies 61, 1994, 631-653

Vaihekoski Mika, 2002 ”Excel ja rahoitusalan sovellukset” 1-2 edition, WSOY Vantaa.

Zeileis Achim, “Econometric Computing with HC and HAC Covariance Matrix Estimators” Journal of Statistical Software 11(10), 1-17

APPENDICES

Appendix 1. Linear Regression – Yield Spread

Number of Observations Read	105
Number of Observations Used	105

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	0.00756	0.00756	14.68	0.0002
Error	103	0.05304	0.00051493		
Corrected Total	104	0.06060			

Root MSE	0.02269	**R-Square**	0.1248
Dependent Mean	0.02679	**Adj R-Sq**	0.1163
Coeff Var	84.68851		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.01277	0.00428	2.98	0.0035
Yield Spread (Lagged)	1	0.79561	0.20764	3.83	0.0002

Test of First and Second Moment Specification		
DF	**Chi-Square**	**Pr > ChiSq**
2	11.42	0.0033

Appendix 2. Linear Regression – PMI

Number of Observations Read	105
Number of Observations Used	105

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	0.00315	0.00315	5.65	0.0193
Error	103	0.05744	0.00055771		
Corrected Total	104	0.06060			

Root MSE	0.02362	**R-Square**	0.0520
Dependent Mean	0.02679	**Adj R-Sq**	0.0428
Coeff Var	88.13662		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-0.03113	0.02447	-1.27	0.2061
PMI	1	0.00112	0.00047167	2.38	0.0193

Test of First and Second Moment Specification		
DF	Chi-Square	Pr > ChiSq
2	5.01	0.0818

Appendix 3. Linear Regression – CCI

Number of Observations Read	105
Number of Observations Used	105

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	0.00540	0.00540	10.08	0.0020
Error	103	0.05519	0.00053586		
Corrected Total	104	0.06060			

Root MSE	0.02315	R-Square	0.0892
Dependent Mean	0.02679	Adj R-Sq	0.0803
Coeff Var	86.39293		

Parameter Estimates					
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	0.02712	0.00226	11.99	<.0001
CCI	1	0.06096	0.01920	3.18	0.0020

Test of First and Second Moment Specification		
DF	Chi-Square	Pr > ChiSq
2	4.96	0.0838

Appendix 4. Multiple Linear Regression

Number of Observations Read	105
Number of Observations Used	105

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	3	0.01075	0.00358	7.26	0.0002
Error	101	0.04984	0.00049350		
Corrected Total	104	0.06060			

Root MSE	0.02221	**R-Square**	0.1775
Dependent Mean	0.02679	**Adj R-Sq**	0.1530
Coeff Var	82.90746		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.00307	0.02520	0.12	0.9031
YS	1	0.65075	0.21671	3.00	0.0034
CCI	1	0.04390	0.02010	2.18	0.0313
PMI	1	0.00024168	0.00050015	0.48	0.6300

Test of First and Second Moment Specification		
DF	**Chi-Square**	**Pr > ChiSq**
9	13.89	0.1261

Appendix 5. Linear Regression with autoregressive Errors – Yield Spread

Ordinary Least Squares Estimates			
SSE	0.05303773	**DFE**	103
MSE	0.0005149	**Root MSE**	0.02269
SBC	-489.73976	**AIC**	-495.04768
MAE	0.0165874	**AICC**	-494.93004
MAPE	503.071147	**HQC**	-492.89681
Durbin-Watson	1.2588	**Regress R-Square**	0.1248
		Total R-Square	0.1248

Durbin-Watson Statistics	
Order	**DW**
1	1.2588

Parameter Estimates					
Variable	**DF**	**Estimate**	**Standard Error**	**t Value**	**Approx Pr > |t|**
Intercept	1	0.0128	0.004278	2.98	0.0035
Yield Spread (Lagged)	1	0.7956	0.2076	3.83	0.0002

Estimates of Autocorrelations			
Lag	**Covariance**	**Correlation**	-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
0	0.000505	1.000000	| |********************|
1	0.000187	0.370555	| |******* |

Preliminary MSE	0.000436

Estimates of Autoregressive Parameters			
Lag	**Coefficient**	**Standard Error**	**t Value**
1	-0.370555	0.091966	-4.03

Maximum Likelihood Estimates			
SSE	0.04573328	**DFE**	102
MSE	0.0004484	**Root MSE**	0.02117
SBC	-500.49837	**AIC**	-508.46026
MAE	0.01619523	**AICC**	-508.22263
MAPE	420.080386	**HQC**	-505.23394
Durbin-Watson	2.1925	**Regress R-Square**	0.0645
		Total R-Square	0.2453

Durbin-Watson Statistics	
Order	**DW**
1	2.1925

Parameter Estimates					
Variable	**DF**	**Estimate**	**Standard Error**	**t Value**	**Approx Pr > |t|**
Intercept	1	0.0138	0.005889	2.35	0.0206
Yield Spread (Lagged)	1	0.7347	0.2773	2.65	0.0093
AR1	1	-0.3686	0.0920	-4.01	0.0001

Autoregressive parameters assumed given					
Variable	**DF**	**Estimate**	**Standard Error**	**t Value**	**Approx Pr > |t|**
Intercept	1	0.0138	0.005885	2.35	0.0206
Yield Spread (Lagged)	1	0.7347	0.2770	2.65	0.0093

Appendix 6. Linear Regression with autoregressive Errors – CCI

Ordinary Least Squares Estimates			
SSE	0.05519406	**DFE**	103
MSE	0.0005359	**Root MSE**	0.02315
SBC	-485.55531	**AIC**	-490.86323
MAE	0.01665194	**AICC**	-490.74558
MAPE	578.838296	**HQC**	-488.71236
Durbin-Watson	1.3548	**Regress R-Square**	0.0892
		Total R-Square	0.0892

Durbin-Watson Statistics	
Order	**DW**
1	1.3548

Parameter Estimates					
Variable	**DF**	**Estimate**	**Standard Error**	**t Value**	**Approx Pr > |t|**
Intercept	1	0.0271	0.002261	11.99	<.0001
CCI	1	0.0610	0.0192	3.18	0.0020

Estimates of Autocorrelations			
Lag	**Covariance**	**Correlation**	-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
0	0.000526	1.000000	| |********************|
1	0.000169	0.322423	| |****** |

Preliminary MSE	0.000471

Estimates of Autoregressive Parameters			
Lag	**Coefficient**	**Standard Error**	**t Value**
1	-0.322423	0.093727	-3.44

Maximum Likelihood Estimates			
SSE	0.04766688	**DFE**	102
MSE	0.0004673	**Root MSE**	0.02162
SBC	-496.11885	**AIC**	-504.08073
MAE	0.01614335	**AICC**	-503.84311
MAPE	528.336104	**HQC**	-500.85442
Durbin-Watson	2.2067	**Regress R-Square**	0.0199
		Total R-Square	0.2134

Durbin-Watson Statistics	
Order	**DW**
1	2.2067

Parameter Estimates					
Variable	**DF**	**Estimate**	**Standard Error**	**t Value**	**Approx Pr > |t|**
Intercept	1	0.0270	0.003513	7.67	<.0001
CCI	1	0.0245	0.0177	1.39	0.1688
AR1	1	-0.4032	0.0939	-4.30	<.0001

Autoregressive parameters assumed given					
Variable	**DF**	**Estimate**	**Standard Error**	**t Value**	**Approx Pr > |t|**
Intercept	1	0.0270	0.003513	7.67	<.0001
CCI	1	0.0245	0.0170	1.44	0.1533

Appendix 7. Linear Regression with autoregressive Errors – PMI

Ordinary Least Squares Estimates			
SSE	0.05744454	**DFE**	103
MSE	0.0005577	**Root MSE**	0.02362
SBC	-481.35903	**AIC**	-486.66695
MAE	0.01688569	**AICC**	-486.5493
MAPE	581.534985	**HQC**	-484.51608
Durbin-Watson	1.1964	**Regress R-Square**	0.0520
		Total R-Square	0.0520

Durbin-Watson Statistics	
Order	**DW**
1	1.1964

Parameter Estimates					
Variable	**DF**	**Estimate**	**Standard Error**	**t Value**	**Approx Pr > |t|**
Intercept	1	-0.0311	0.0245	-1.27	0.2061
PMI	1	0.001122	0.000472	2.38	0.0193

Estimates of Autocorrelations			
Lag	**Covariance**	**Correlation**	-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
0	0.000547	1.000000	| |********************|
1	0.000220	0.401703	| |******** |

Preliminary MSE	0.000459

Estimates of Autoregressive Parameters			
Lag	**Coefficient**	**Standard Error**	**t Value**
1	-0.401703	0.090675	-4.43

Maximum Likelihood Estimates			
SSE	0.04795673	**DFE**	102
MSE	0.0004702	**Root MSE**	0.02168
SBC	-495.47558	**AIC**	-503.43746
MAE	0.01621555	**AICC**	-503.19984
MAPE	538.116545	**HQC**	-500.21115
Durbin-Watson	2.1800	**Regress R-Square**	0.0132
		Total R-Square	0.2086

Durbin-Watson Statistics	
Order	**DW**
1	2.1800

Parameter Estimates					
Variable	**DF**	**Estimate**	**Standard Error**	**t Value**	**Approx Pr > |t|**
Intercept	1	-0.009740	0.0332	-0.29	0.7698
PMI	1	0.000707	0.000638	1.11	0.2700
AR1	1	-0.4101	0.0951	-4.31	<.0001

Autoregressive parameters assumed given					
Variable	**DF**	**Estimate**	**Standard Error**	**t Value**	**Approx Pr > |t|**
Intercept	1	-0.009740	0.0315	-0.31	0.7578
PMI	1	0.000707	0.000605	1.17	0.2449

Appendix 8. Linear Regression with autoregressive Errors – Multi Linear Regression

Ordinary Least Squares Estimates			
SSE	0.04984336	**DFE**	101
MSE	0.0004935	**Root MSE**	0.02221
SBC	-486.95425	**AIC**	-497.57009
MAE	0.0163173	**AICC**	-497.17009
MAPE	471.06422	**HQC**	-493.26834
Durbin-Watson	1.4011	**Regress R-Square**	0.1775
		Total R-Square	0.1775

Durbin-Watson Statistics	
Order	**DW**
1	1.4011

Parameter Estimates					
Variable	**DF**	**Estimate**	**Standard Error**	**t Value**	**Approx Pr > |t|**
Intercept	1	0.003075	0.0252	0.12	0.9031
YS	1	0.6507	0.2167	3.00	0.0034
CCI	1	0.0439	0.0201	2.18	0.0313
PMI	1	0.000242	0.000500	0.48	0.6300

Estimates of Autocorrelations			
Lag	**Covariance**	**Correlation**	-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
0	0.000475	1.000000	| |********************|
1	0.000142	0.298906	| |****** |

Preliminary MSE	0.000432

Estimates of Autoregressive Parameters			
Lag	**Coefficient**	**Standard Error**	**t Value**
1	-0.298906	0.095428	-3.13

Maximum Likelihood Estimates			
SSE	0.04477198	**DFE**	100
MSE	0.0004477	**Root MSE**	0.02116
SBC	-493.44997	**AIC**	-506.71977
MAE	0.01598893	**AICC**	-506.11371
MAPE	411.916023	**HQC**	-501.34258
Durbin-Watson	2.1500	**Regress R-Square**	0.0920
		Total R-Square	0.2612

Durbin-Watson Statistics	
Order	**DW**
1	2.1500

Parameter Estimates					
Variable	**DF**	**Estimate**	**Standard Error**	**t Value**	**Approx Pr > |t|**
Intercept	1	0.002808	0.0309	0.09	0.9278
YS	1	0.6804	0.2757	2.47	0.0153
CCI	1	0.0231	0.0182	1.27	0.2080
PMI	1	0.000234	0.000610	0.38	0.7020
AR1	1	-0.3324	0.0987	-3.37	0.0011

Autoregressive parameters assumed given					
Variable	**DF**	**Estimate**	**Standard Error**	**t Value**	**Approx Pr > |t|**
Intercept	1	0.002808	0.0305	0.09	0.9268
YS	1	0.6804	0.2753	2.47	0.0152
CCI	1	0.0231	0.0179	1.29	0.1996
PMI	1	0.000234	0.000601	0.39	0.6976

Appendix 9. Cross Correlations between the indicators

Pearson Correlation Coefficients, N = 104 Prob > |r| under H0: Rho=0	
	PMI
CCI	0.38712 <.0001

Pearson Correlation Coefficients, N = 104 Prob > |r| under H0: Rho=0	
	PMI
YS	0.16427 0.0956

Pearson Correlation Coefficients, N = 104 Prob > |r| under H0: Rho=0	
	CCI
YS	0.11313 0.2528

Appendix 10. Yield Spread Regression with Newey-West Correction

```
Allocate 105
Open data Z:\Gradu\Regressio\RegressioYS.txt
Data(format=free   org=obs) 1 105 y1 x1

linreg(robusterrors lags=0              lwindow=neweywest) y1
#constant x1

Linear Regression - Estimation by Least Squares
Robust Standard Error Calculations
Dependent Variable Y1
Usable Observations    105      Degrees of Freedom   103
Centered R**2     0.124762      R Bar **2   0.116264
Uncentered R**2   0.609970      T x R**2      64.047
Mean of Dependent Variable      0.0267947284
Std Error of Dependent Variable 0.0241386324
Standard Error of Estimate      0.0226920554
Sum of Squared Residuals        0.0530377262
Log Likelihood                  249.52384
Durbin-Watson Statistic         1.258850

  Variable            Coeff            Std Error        T-Stat       Signif
*******************************************************************************
1.  Constant          0.0127681100   0.0060681721   2.10411      0.03536873
2.  X1                0.7956053921   0.2536302660   3.13687      0.00170761
```

Appendix 11. PMI Regression with Newey-West Correction

```
Allocate 105
Open data Z:\Gradu\Regressio\RegressioPMI.txt
Data(format=free   org=obs) 1 105 y1 x1

linreg(robusterrors lags=0      lwindow=neweywest) y1
#constant x1

Linear Regression - Estimation by Least Squares
Robust Standard Error Calculations
Dependent Variable Y1
Usable Observations    105      Degrees of Freedom   103
Centered R**2     0.052040      R Bar **2   0.042836
Uncentered R**2   0.577563      T x R**2      60.644
Mean of Dependent Variable      0.0267947284
Std Error of Dependent Variable 0.0241386324
Standard Error of Estimate      0.0236159690
Sum of Squared Residuals        0.0574445414
Log Likelihood                  245.33348
Durbin-Watson Statistic         1.196372

Variable            Coeff        Std Error      T-Stat        Signif
*****************************************************************************
1. Constant         -0.0311309   0.020818382    -1.49536      0.13482140
2. X1               0.0011215    0.000386620    2.90097       0.00372005
```

Appendix 12. CCI Regression with Newey-West Correction

```
Allocate 105
Open data Z:\Gradu\Regressio\RegressioCCI.txt
Data(format=free   org=obs) 1 105 y1 x1

linreg(robusterrors lags=0      lwindow=neweywest) y1
#constant x1

Linear Regression - Estimation by Least Squares
Robust Standard Error Calculations
Dependent Variable Y1
Usable Observations    105      Degrees of Freedom   103
Centered R**2     0.089178      R Bar **2   0.080335
Uncentered R**2   0.594112      T x R**2      62.382
Mean of Dependent Variable      0.0267947284
Std Error of Dependent Variable 0.0241386324
Standard Error of Estimate      0.0231487517
Sum of Squared Residuals        0.0551940646
Log Likelihood                  247.43161
Durbin-Watson Statistic         1.354790

Variable            Coeff       Std Error      T-Stat        Signif
*******************************************************************************
1. Constant         0.0271204   0.0021910325   12.37794      0.00000000
2. X1               0.0609595   0.0225696823   2.70095       0.00691419
```

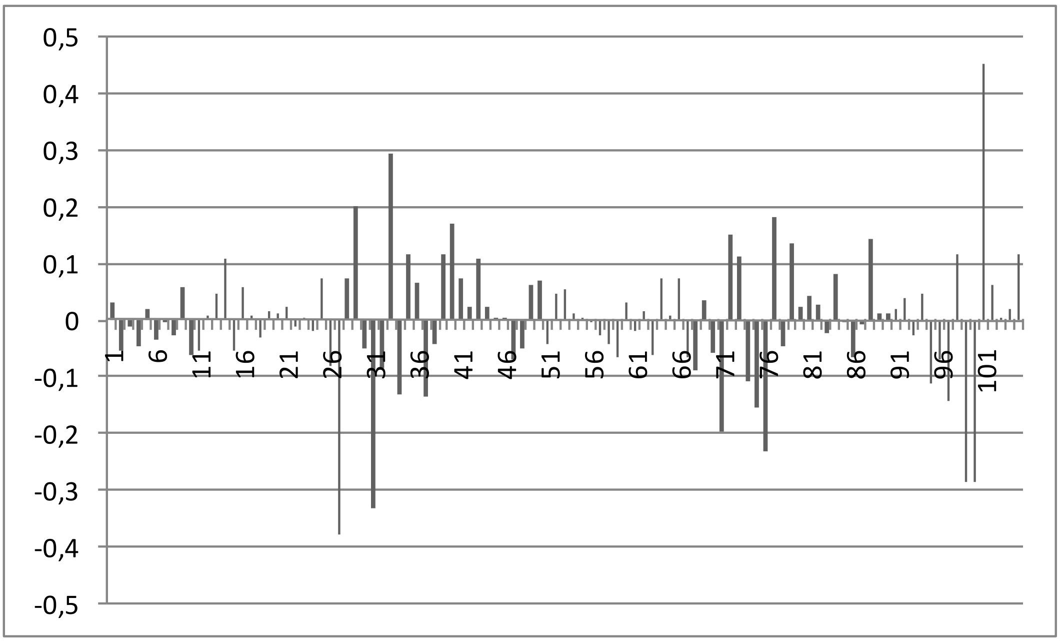
Appendix 13. Multiple Linear Regression with Newey-West Correction

```
Open data Z:\Gradu\Regressio\Regressiomu.txt
Data(format=free   org=obs) 1 105 y1 x1 x2 x3

linreg(robusterrors lags=0            lwindow=neweywest) y1
#constant x1 x2 x3

Linear Regression - Estimation by Least Squares
Robust Standard Error Calculations
Dependent Variable Y1
Usable Observations    105      Degrees of Freedom   101
Centered R**2     0.177476      R Bar **2   0.153044
Uncentered R**2   0.633460      T x R**2      66.513
Mean of Dependent Variable      0.0267947284
Std Error of Dependent Variable 0.0241386324
Standard Error of Estimate      0.0222148295
Sum of Squared Residuals        0.0498433636
Log Likelihood                  252.78504
Durbin-Watson Statistic         1.401137

Variable        Coeff           Std Error       T-Stat      Signif
*******************************************************************************
Constant        0.0030746625    0.0198584698    0.15483     0.87695631
X1              0.6507462187    0.2558948590    2.54302     0.01098984
X2              0.0438966291    0.0208738356    2.10295     0.03547016
X3              0.0002416788    0.0004257150    0.56770     0.57023815
```

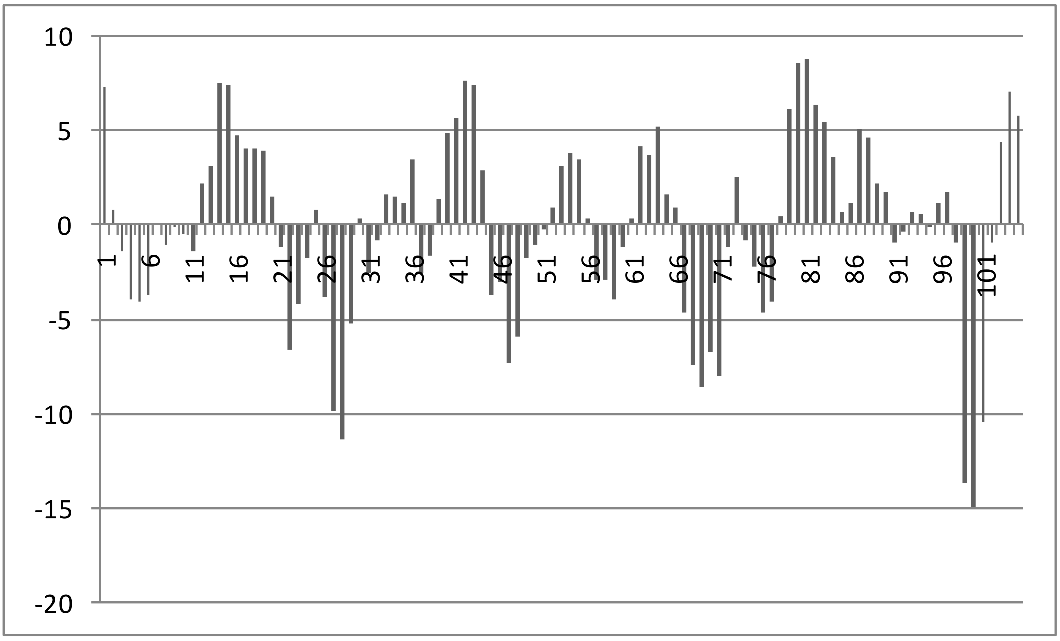
Appendix 14. VBA-Code done in Excel to calculate the put option margins

```
Function CallPrice(S, X, Sigma, r, Time, Delta)

CallPrice = S * WorksheetFunction.NormSDist(d_1(S, X, Sigma, r, Time, Delta)) _

 * Exp(-Delta * Time) - X * Exp(-Time * r) _

  * WorksheetFunction.NormSDist(d_2(S, X, Sigma, r, Time, Delta))

End Function

Function PutPrice(S, X, Sigma, r, Time, Delta)

PutPrice = CallPrice(S, X, Sigma, r, Time, Delta) + X * Exp(-r * Time) - S

End Function

Function d_1(S, X, Sigma, r, Time, Delta)

d_1 = (Log(S / X) + (r - Delta + 0.5 * Sigma ^ 2) * Time) / (Sigma * Sqr(Time))

End Function

Function d_2(S, X, Sigma, r, Time, Delta)

d_2 = d_1(S, X, Sigma, r, Time, Delta) - Sigma * Sqr(Time)

End Function
```

Appendix 15. Histograms for PMI and CCI linear regressions residuals



Histogram of the classical linear regression residuals for CCI



Histogram of the classical linear regression residuals for PMI