A Reexamination of Time-Varying Stock Return Predictability

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Abstract

In predicting stock market returns, academic research has had its primary focus on macroeconomic variables, and less attention has been paid towards technical indicators. The evidence of the stock return predictability is either absent or weak, and there are cases of contradicting evidence in the literature whether stock returns even are predictable. Over the last ten years, several papers find evidence that stock return predictability exists during the bad economic states. These papers have used different approaches, whereas most of them have been using NBER chronology of expansions and recessions, or investor sentiment index, to define good and bad economic times. Based on our knowledge, there has been limited research regarding the use of bull and bear markets to determine these market states. This thesis reexamines and extends previous studies on the time-varying stock return predictability. Our research is similar to Huang et al. (2014), as we measure the performance of different predictors by conducting a Newey-West-statistics derived from one-state and two-state predictive regression for the in-sample forecast. However, our thesis is extended by using four different definitions of market states to examine whether there is significant evidence of stock return predictability. Result of this thesis presents a mixed performance across the different macroeconomic variables and technical indicators. Most of the predictors perform better in bull and bear markets compared to expansions and recessions, and investor sentiment index. We have tried to compare our results to previous studies, but each study applied a combination of different datasets, approaches, and methodologies, and therefore, it would be impractical to compare the findings.

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1 Introduction

Stock return predictability has been a popular topic amongst researchers in the field of economics and finance for many years. One could argue that stock price has almost the same probability distribution as a particle in Geometric Brownian motion. This model for the continuous-time stochastic process has been used by Black and Scholes in mathematical finance to model stock prices as early as in the 1960s. A critical assumption of the Black and Scholes formula is that the market follows the efficient market hypothesis. This hypothesis has been described in the groundbreaking research by Malkiel and Fama (1970), where they stated that the prices in the market reflect all the available information, and therefore it is impossible to beat the market.

A great deal of econometric research has been devoted to examining whether it is possible to beat the market. Different articles used various methods, variables, and time periods in an attempt to predict the market. Some of the findings contradict each other, and it appears to be a publication bias in favor of the impression that prediction works; hence, one is less attracted to articles that show no evidence of predictability. However, Lettau and Ludvigson (2001) summarized the prevailing tone in the literature as "It is now widely accepted that excess returns are predictable by variables such as dividend-price ratios, earnings-price ratios, dividend-earnings ratios, and an assortment of other financial indicators."

There is a long list of literature focusing on forecasting the stock market returns with different predictive variables of price multiples, macroeconomic variables, corporate actions, and measures of risk. An important research paper on this topic is written by Welch and Goyal (2008), who did an extensive study about the performance of the macroeconomic variables suggested by academic literature to be good predictors of the stock returns. They diagnosed the performance of each variable for both in-sample and out-of-sample forecast and concluded that most of the variables are unstable, and most of them are no longer significant for an in-sample forecast. On the contrary, several authors such as Inoue and Kilian (2004) and Cochrane (2007) argued that this could not prove as evidence against stock returns predictability. However, it is evidence of the difficulty in exploiting predictability with trading strategies.

Most of the attention has been in favor of macroeconomic variables to predict the stock market returns, and relatively little attention has been spent towards technical indicators, despite the fact that these have been used among practitioners. Neely et al. (2014) compared the forecasting ability of technical indicators with well-known macroeconomic variables that have been mentioned in Welch and Goyal (2008). Their study presented that these technical indicators displayed statistical significance in- and out-of-sample forecasting power that is matching or exceeding that of macroeconomic variables. Furthermore, there is evidence that these two types of indicators provide complementary information over the business cycle. It was stated by (Neely et al.,2014,p.2) as "Technical indicators better detect the typical decline in the equity risk premium near business-cycle peaks, while macroeconomic variables more readily pick up the typical rise in the equity risk premium near cyclical troughs." Their conclusion emphasizes that one should combine the information from both technical indicators and macroeconomic variables. This is in order to significantly improve the predictability of stock market returns, rather than using either type of information alone.

However, in recent years, several respectable finance researchers have conducted studies on the subject of time-varying stock return predictability and demonstrated that the stock return predictability is mostly concentrated in times of economic recessions. NBER chronology of recessions and expansions has been frequently used amongst authors to define good and bad economic times. For instance, Gonzalo and Pitarakis (2012) argue that the predictability of stock return may vary across different phases of cycles. In addition, by using NBER chronology, Rapach et al. (2010), Henkel et al. (2011), and Dangl and Halling (2012) found evidence that return predictability only exists during recession periods. Nevertheless, there is contradicting evidence in the literature, whether stock returns are even predictable in either of the states. In addition, researchers have been analyzing human psychology and thereby paid more attention to investor sentiment and how it may affect asset prices. Baker and Wurgler (2006) measure an investor sentiment index that aggregates the information from six proxies. Their study shows that those with high investor sentiment does predict lower returns for speculative stocks that are difficult to exploit by arbitrage opportunities.

Most of the previous studies have shown significant evidence of predictability at a minimum of one-year time-period or even several years, but few have focused on whether one can predict the stock market by using monthly frequency. Another interesting question is to analyze how one can use bull and bear market in combination with macroeconomic and technical predictor variables to predict the stock market. This is a relatively novel approach, and currently, the literature on this problem is limited.

This thesis reexamines and extends previous studies on the time-varying stock return predictability. We are going to use four different definitions of market states to examine whether there exists significant evidence of stock return predictability in various market states. This study is similar to Huang et al. (2014) as we measure the performance of different predictors by conducting a Newey-West t-statistics derived from one-state and two-state predictive regression for the in-sample forecast. We will only use in-sample predictability since good and bad economic states cannot be detected in real time, because they are detected as posteriori. Finally, we will conduct a robustness test by splitting the total sample period into two equal subperiods and estimate the regression for each part. The main goal is to see whether the results for the entire dataset still applies in these subperiods.

We use monthly data spanning from January 1867 to December 2017 for 12 well-known macroeconomic variables that are mentioned in Welch and Goyal (2008). This dataset is the updated version of the one that has been used in their study. Further, we will implement an additional four technical indicators of moving averages, momentum rule, past monthly return, and conditional variance, which are good indicators to describe the dynamics in the stock market. For definitions of the market states, we are using the data provided by NBER for economic recessions and expansions, bull and bear states of the stock market from Zakamulin (2017) and investor sentiment states from Baker and Wurgler (2007).

Our results show mixed performance across the different macroeconomic variables and technical indicators. Firstly, very few variables show a convincing performance of predicting the stock return by excluding the market states. Only two out of 12 macroeconomic variables are significant at the 10%, and only one technical indicator is significant at the 1% level in predicting the stock returns. Secondly, most of the predictors are performing better in bull and bear market compared to NBER chronology of market states and investor sentiment index.

The rest of the thesis is organized as follows: Section 2 reviews the relevant literature to understand the background for our research and how it extends existing research.

Section 3 considers the data, data sources, and sample period for our analysis. In this section, we also present descriptive statistics. Section 4 describes the methods used for regression analysis, performance measures, statistical estimations, and tests that we use. Section 5 summarizes and presents results. Section 6 discusses our empirical results in compliance with previous literature. Finally, Section 7 recap our thesis with the conclusion and final remarks.

2 Literature review

In the past century, statisticians noticed that changes in stock prices seem to follow a fair-game pattern. This behavior of stock prices was the foundation of the random walk hypothesis. It was first introduced by Bachelier (1900) who believed that a random process determines stock prices. He compared this process to the steps taken by a drunk man who is expected to stagger in a totally unpredictable and random fashion. This hypothesis was studied and intensely debated in the 1960s. Five years later, Fama (1965) published empirical work on the efficient market hypothesis that presented consistent and strong support for the model. The research conducted by Samuelson (1965), and Fama (1965) indicated that correctly anticipated prices fluctuate randomly, which means that the prices in the efficient market reflect all the available information, and therefore it is impossible to beat the market without taking on any risk. Black and Scholes (1973) applied the assumptions of the efficient market hypothesis to derive one of the most fundamental concepts in a modern financial theory known as the Black-Scholes model. This model assumes ideal conditions in the market and gives an estimate of the price of European options.

However, performing tests on market efficiency appear to be complicated. Several studies have proved some anomalous behavior that seems to be inconsistent with market efficiency. Ball (1978) argued that this evidence could be interpreted as an indication of shortcomings in the current model of expected returns. Fama (1997) supported this argument and stated that the apparent anomalies do require new behaviourally based theories of the stock market. This model was viewed as an uncompleted model of asset pricing, and therefore, they were indicative of a need to continue the search for better models. For the past quarter of a century, several papers have argued against the efficient market hypothesis. For instance, Roll and Ross (1994) observed that it is almost impossible to profit from even the most extreme violations of market efficiency. This can be explained by the fact that stock market anomalies are considered as stochastic processes that do not persist in the future.

Welch and Goyal (2008) reexamined the empirical evidence of stock return prediction by investigating the in-sample and out-of-sample performance of linear regressions that predict the equity premium with prominent variables. They analyzed how these variables can predict the equity premium, but also demonstrated how the investor's decision-making process could improve portfolio allocation. They concluded that most of the variables are unstable or even false, and some of them are no longer significant for an in-sample forecast. Also, the out-sample performance has been particularly poor for predictive regressions in the past few decades, and none have overperformed after the oil shock in the 1970s.

Most of the attention has been in favor of macroeconomic variables to predict the stock market returns. However, there is relatively little attention towards technical indicators despite that these are used amongst investors today. Technical analysts attempt to forecast prices by using different trading techniques. For instance, a trend following strategy is typically based on switching between the market and the cash, depending on whether the market prices trend upward or downward. When the strategy identifies that prices trends upward or downward, it generates a buy or sell trading signal. As Brock et al. (1992) described, technical analysis is the original form of investment analysis that started in the 1800s. Many of these techniques were developed 60 years ago, and are still used today.

There is a vast amount of literature, questioning whether it is possible to validate the efficient market hypothesis. De Bondt and Thaler (1985), Fama and French (1986), Poterba and Summers (1988), Chopra et al. (1992), amongst many others, presents evidence of predictability of equity returns from past returns. However, these studies are in sharp contrast with some earlier studies that supported the random walk hypothesis. In contrast to supporting this hypothesis, they find that the predictable variation in equity returns are minimal. Although some earlier studies do not find technical variables to be useful on the predictability of equity returns from past returns, recent studies such as Alexander (1961), Fama and Blume (1966), Levy (1967a), Levy (1967b), Jensen (1967), and Jensen and Benington (1970), suggest that this might be premature to conclude. An important research article about technical trading rules was written by Brock et al. (1992). In this article, they investigated two of the most common trading rules, which are moving averages and trading-range breaks. In their first method, buy and sell signals are generated by two moving averages, which are a long period and a short period. In the second method, their signals are generated as stock prices hit new highs and lows. These rules are evaluated by their ability to forecast future price changes. Their study finds evidence that predictability of stock prices change by using these technical trading rules, and they observed that returns during buy periods are more substantial but less volatile compared to returns during sell periods.

In the last ten years, researchers have been evaluating the predictability of stock returns in different market states. Some studies find evidence of time-varying dynamics relationships between predictors and expected returns. The business cycles are, therefore, considered to be an essential factor in describing the complex behavior of the predictors. In the literature there exist studies such as Campbell and Cochrane (1999), Menzly et al. (2004) and Baker and Wurgler (2007) that show evidence of risk premiums are countercyclical, and the time-series behavior of risk premiums dictates some of the return predictability. Fama and French (1989) and Ferson and Harvey (1991) find empirical evidence of countercyclical risk premium in their research too. Another study conducted by Henkel et al. (2011) estimated that the market risk premium is higher during recessions in all of the G7 countries except Germany. However, Campbell and Cochrane (1999) believed that the cyclical dynamics might not need to be synchronous since changing the risk aversion alone would be insufficient to affect any return predictability.

Recently there has been growing popularity amongst academics to investigate the effect of individual investor sentiment on stock returns. Diether et al. (2002) and Tetlock (2007) point out the disagreement amongst investors and their reactions to the news seems to predict future returns. Further, Cen et al. (2013) and Garcia (2013) find evidence that investor disagreement and content of news does predict the stock return in bad economic times. However, it is unclear what kind of mechanism that causes return predictability to vary over the business cycle. One crucial factor is that investors learn at different speeds regarding the news. Those investors that are fast learners are focusing on sharp variations in the business cycles, while slow learners are more concentrate on long-term fluctuations. Once the difference in learning speeds increases, it would cause disagreement amongst investors to spike, and prices are continuing to react to past news, which causes deterioration in the economic conditions. Therefore, the stock return predictability is concentrated in bad economic times, as stated by Patton and Timmermann (2010). Even though investors are observing the same information, the disagreement amongst them may occur because they use different models and have a different interpretation of the data. Their economic conditions play a significant role in their learning differences, which may lead to a pattern of disagreement that is changing over the business cycle. However, Patton and Timmermann (2010) find that the adjustment of expectations is at comparable speeds, and disagreement exhibits little variation in good economic times. Nonetheless, there might be some implications with investor sentiment index since this phenomenon is difficult to observe. We are using the method proposed by Baker and Wurgler (2007), which has been widely used in academic research. It is based on a principal component analysis with six proxies from market data.

In the literature, most research has been utilizing on NBER chronology of recessions and expansions or investor sentiment index to define good and bad economic times. However, there exist relatively few research papers on bull and bear markets. Zakamulin pointed out that bull and bear markets are highly overlooked by researchers, and argued that it has many advantages over other methods previously described. We examine these claims and explain the differences in Section 6.

3 Data

3.1 Return and prices

The S&P 500 index returns used by Welch and Goyal (2008) for the period 1926 to 2005 are from the Center for Research in Security Press (CRSP) for month-end values. It is the continuously compounded returns on the S&P 500 index that includes dividends. The data for yearly and longer frequencies prior to 1926 is from Robert Shiller's [1].

The risk-free rate from 1920 to 2005 is the Treasury-bill rate. Welch and Goyal (2008) estimated the risk-free short-term debt prior to the 1920s. Commercial paper rates for New York City are from the National Bureau of Economic Research (NBER) Macrohistory database. These commercial paper rates are available from 1871 to 1970. They estimated the regression for 1920-1971 by the following equation:

$$Treasury - bill\, rate = -0.004 + 0.886 \cdot Commercial\, Paper\, Rate, \qquad (1)$$

thereafter, the risk-free rate from 1871-1919 was instrumented with the predicted regression equation. The correlation for the period 1920-1971 between the equity premium was computed by using the actual Treasury-bill rate. However, this Treasury-bill rate was computed by using the predicted Treasury-bill rate from the commercial paper rate.

However, the data for our empirical analysis consists of monthly S&P Composite index, which is the updated version of the one used by Welch and Goyal (2008)[2]. This version is updated up to 2017. Also, they used time-averaged prices prior to 1925, which led to the problem of the autocorrelation of the monthly returns. This problem resulted in unrealistic high predictability of stock returns. Therefore, to avoid complication, we used the dataset from Schwert (1989) for the period 1871-1925[3]. The data consists of point-sampled prices rather than the time-averaged price, which is a more appropriate method for our analysis. Hence, our monthly return is different from the one used in Welch and Goyal (2008). The monthly stock return at time t is computed as follows:

[1] `http://www.econ.yale.edu/~shiller/`
[2] `http://www.hec.unil.ch/agoyal/`
[3] `http://schwert.ssb.rochester.edu/mstock.htm`

$$r_t = ln\left(\frac{P_t}{P_{t-1}}\right), \tag{2}$$

where P_{t} is the price of the monthly composite index at month t.

Table 1 reports a compile of statistics for the monthly S&P Composite index for the whole period from January 1871 to December 2017. We also divided data into two equal subperiods to see if there are any differences. The first subperiod begins in January 1871 and last until June 1944, and the second subperiod is from July 1944 to December 2017. We conducted a Shapiro-Wilk test to tests the null hypothesis to see whether the sample of monthly S&P Composite index is normally distributed. All corresponding p-values are 0.00, which is less than a significant level of 5%. Therefore, one can reject the null hypothesis, and there exists evidence that the data is not normally distributed. Also, while the total market return, capital gain return, and risk-free return are increasing from first to the second period, the standard deviation is decreasing over time.

Table 2 reports a simple representation of data distribution of good and bad economic states. Recessions and expansions, bull and bear market states have a total sampling period that ranges from January 1871 to December 2017. However, the investor sentiment index has a shorter sampling period that ranges from July 1965 to September 2015. The main point to reach from this table is that the percentage distribution varies for each market state. Recessions and expansions have the highest variety, followed by bull and bear, and lastly investor sentiment.

Table 1: S&P Composite Index

Statistics	1871-2017			1871-1944			1944-2017		
	CAP	TOT	RF	CAP	TOT	RF	CAP	TOT	RF
N		1764			882			882	
Mean %	0.65	0.84	0.30	0.61	0.70	0.28	0.69	0.97	0.33
Std. Dev. %	4.97	4.72	0.22	5.69	5.24	0.16	4.11	4.12	0.26
Min %	-29.94	-29.43	0.00	-29.94	-29.43	0.00	-21.76	-21.54	0.00
Max %	42.22	42.91	1.36	42.22	42.91	1.17	16.30	16.78	1.36
Shapiro Wilk	11.05	11.57	11.08	9.86	10.78	9.44	5.38	5.39	9.09
Swilk p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Descriptive statistics for monthly S&P Composite Index for three sample periods. TOT denotes the total market return, CAP denotes the capital gain return, and RF denotes the risk-free return. Shapiro-Wilk represents the test statistic for the normality.

Table 2: Data distribution

Bad state	%	N	Good state	%	N
Recessions	28.34	500	Expansions	71.66	1264
Bear	35.15	620	Bull	63.85	1144
Sentiment under hist. mean	45.94	277	Sentiment over hist. mean	54.06	326
Sentiment decreasing	48.59	293	Sentiment increasing	51.41	310

The distribution of good and bad economic state. % denotes percent distribution in the time-series, N shows a number of observations over the whole time period.

3.2 Macroeconomic indicators

There is a long list of literature focusing on forecasting the stock market returns with different predictive variables of price multiples, macroeconomic variables, corporate actions, and measures of risk. Studies such as Ang et al. (2007), Hodrick (1992), Campbell and Shiller (1988), and Fama and French (1988), used the dividend yield to predict the stock returns. Lamont (1998) and Campbell and Shiller (1988) examined the earnings-price ratio. Pontiff and Schall (1998) and Kothari and Shanken (1997) conducted studies using the book-to-market ratio. The short-term interest rate was presented by Ang et al. (2007), Breen et al. (1989), Fama and Schwert (1977) and Campbell (1987). Tripathi and Kumar (2014) examined the effect of inflation in their study. The term spread, default yield spread, long term rate of return, and corporate issuing activity have been used by Welch and Goyal (2008). They all find evidence in favor of predicting the stock returns in-sample. However, several authors such as Torous et al. (2004), Lewellen (2004), Nelson and Kim (1993), Cavanagh et al. (1995) have questioned these findings due to the persistence of the forecasting variables and the correlation with returns might bias the regression coefficients.

Most of the macroeconomic indicators were available in the dataset used by Welch and Goyal (2008). The following paragraph will briefly describe the data sources and construction of the models as presented by Welch and Goyal (2008). Their first set of independent variables are related to the characteristics of stocks. Dividends that start in 1871 to 1987 are taken from Robert Shiller's website[4], but for 1988-2017 are from the S&P Corporation. Dividends are computed 12-month moving sums of dividends on the S&P

[4] `https://www.econ.yale.edu//~shiller/data.htm`

500 index. *The dividend-to-price ratio* is defined by taking the difference between the log of dividends and the log of prices. *The dividend yield* is calculated by taking the difference between the log of dividends and the log of lagged prices, and *the dividend payout ratio* is the difference between the log of dividends and the log of earnings (Campbell, 1987).

Earnings are also 12-month moving sums of earnings on the index. The data is from the same website for the period 1871 to 1987. Welch and Goyal (2008) have estimated earnings from 1988 to 2017 by using an interpolation method of quarterly earnings provided by the S&P Corporation. *Earning-to-price ratio* is the difference between the log of earnings and the log of prices.

Book values are from 1920 to 2017, and it is from Value Line's website[5] that describes their Long-Term Perspective Chart of the Dow Jones Industrial Average. *The book-to-market ratio* is the ratio of book value to market value for the Dow Jones Industrial Average. If we look at the period from March to December, book-to-market-ratio is computed by dividing book value at the end of the previous year by the price at the end of the current month. For January and February, it is computed by dividing book value at the end of two years ago by the price at the end of the current month (Kothari and Shanken (1997) and Pontiff and Schall (1998)).

Cross-sectional premium measures the relative valuations of high- and low-beta stocks. The data is from Polk et al. (2006), and it is available from May 1937 to December 2002.

There are two measures of Corporate Issuing Activity. The first measure is *equity expansion*, which is the ratio of twelve-month moving sums of net issues by NYSE listed stocks divided by the total market capitalization of NYSE stocks. The data is from 1926 to 2017. The second measure is *percent equity issuing*, which is the ratio of equity issuing activity as a fraction of total issuing activity. Baker and Wurgler (2000) provided the data. The first measure is relative to the aggregate market cap, while the second is relative to aggregate corporate issuing.

Their next set of independent variables are related to interest-rate. *Treasury bills* rates from 1920 to 1933 are the U.S Yields on Short Term Securities, Three-Six Month Treasury Notes and Certificates, Three Month Treasury series from NBER's Macrohistory

[5] `https://fred.stlouisfed.org`

database[6], while from 1934 to 2017 is the 3-Month Treasury Bill from economic research database at Federal Reserve Bank at St.Louis[6].

Long term yield from 1919 to 1925 is the U.S Yields On Long-Term United States Bonds series are taken from NBER's Macrohistory database[6]. Yields that range from 1926 to 2017 are from Ibbotson's Stocks, Bills, Bonds and Inflation Yearbook. *Long term rate of return*, which are long term government bond returns and came from the same database. *The term spread* is the difference between the treasury bills and the government long term yield.

Corporate Bond Yields on AAA- and BAA-rated bonds from 1919 to 2017 are from FRED[6]. *The default yield spread* is calculated by taking the difference between AAA- and BAA-rated corporate bonds yields. *The default return spread* is the difference between the return on long-term corporate bonds and returns on the long-term government bonds.

Inflation is based on the Consumer Price Index for 1919 to 2017 that is taken from the Bureau of Labor Statistics[7]. The information of inflation is released only in the following month, and therefore, Welch and Goyal (2008) calculated one month of waiting for their monthly regressions.

3.3 Technical indicators

We assume that prices move in trends, and by identifying the proper times for buying and selling stocks, we can profit from it. In general, one can implement a simple trend following strategy by buying (selling) assets if there is any indication that these assets will be trending upward (downward) shortly. The simple concept of trend following might be challenging to implement in practice due to price fluctuations. One can implement moving averages to identify whether it is an upward or downward trend and use this technical indicator to remove the noise from large price fluctuations. According to Brock et al. (1992) and Zakamulin (2017), moving averages are one of the simplest and most common ways to time the market and detect the underlying trend.

[6] `https://fred.stlouisfed.org`
[7] `https://www.bls.gov/cpi/`

3.3.1 Moving Averages

According to Siegel (1994), the moving averages are a popular appliance for determining when the trend might change and examines the relationship between the current price and a moving average of past price movements. A moving average is the arithmetic average of a given stock or index price over a fixed interval. There are different types of moving average weighting schemes. Simple Moving Average (SMA) is the most common type of moving averages where each price observation is equally weighted. Some analysts hold a belief that the most recent stock prices observations might contain more relevant information on the future direction of the stock price than earlier stock prices. Zakamulin (2017) showed that for this idea to work, one needs to substitute the SMA with the Linear Moving Average (LMA) where the weight of each price decreases in an arithmetic sequence. If the arithmetic weighting-scheme in the LMA is too rigid, then another alternative for investors is to use the Exponential Moving Average (EMA). This means the price observations in this Exponential Moving Average are weighted exponentially.

A common approach is to use 200-day moving average when using daily data (or 10-month moving average when data is on a monthly basis). It uses the information for the last 200 days (10-months) of closing prices. The advantage of using moving averages over one-point prices is that they fluctuate far less, in addition to giving the trader room for technical analysis. This also allows for identifying market trends by reducing the noise of daily (monthly) pricing. Note that there is not one size fit all solution, but the longer the time frame used, the smoother the moving average function will be. A shorter moving average is more volatile, but the readings are closer to the origin.

Instead of using the simple formula of averaging prices, we are using an alternative form suggested by Acar (1998) and Zakamulin (2017). An alternative representation of the computation of the trading indicator is given by equation (2), which motivates the computation of the moving average to be approximated using the returns instead of price changes. The main advantage of using this approach is that one can remove the risk of stationary of time series data, as stock prices are increasing over time.

The alternative method of computing moving average at time t of the last ten observed prices can be defined as:

$$SMA_t(\mathit{10}) = \sum_{i=0}^{9}(10 - i) \cdot r_{t-i}, \tag{3}$$

where r_{t-i} denotes the log return of the previous period, and $(10-i)$ is weighing function for returns on the simple moving average rule.

3.3.2 Momentum rule

The Momentum rule is one of the simplest and most basic market timing rules. This rule compares the last closing price with the closing price n-1 periods ago. If the last closing price is higher than the closing price n-1 periods ago, then it is an indication for *a buy signal*. This rule holds if one can observe that the market prices have been increasing or decreasing over the last n-1 periods, then one can assume that the prices will continue to increase or decrease over the subsequent period. This means we will most likely observe the n-1 trend will continue in the future (Zakamulin,2007,p.67). Moskowitz et al. (2012) and Antonacci (2014) were the ones that looked at some of the advantages of the momentum rule strategy. The results have shown persistence in returns for one to 12 months, over a long time period. We chose to use 12 months of lagged values as it uses the longest time horizon.

Zakamulin (2017) demonstrated that momentum rule could be computed in a similar way as moving averages:

$$MOM_t(\mathit{12}) = \sum_{i=0}^{11} r_{t-i}, \tag{4}$$

where r_{t-i} denotes the log return of the previous period and n-1 periods ago, in an equally weighted form.

3.3.3 Conditional variance

Most investors wish to make a portfolio that offers the highest returns with the lowest possible risk. If volatility spikes, we would assume that uncertainty grows among investors. This could have a domino effect following more volatility and uncertainty. French et al. (1987) stated that unexpected stock market returns are negatively related to the unexpected change in the volatility of stock returns. Therefore, we would expect a negative coefficient in bad economic times. Goyal and Welch (2008) used a conditional variance, which is computed as a sum of squared daily returns on the S&P 500 index. Daily returns were provided by Schwert (1989) for the period 1871-1926[8], and for the second period, 1926-2017 are from CRSP[9].

3.3.4 Past monthly return

Like conditional variance, we assume that past monthly return has an impact on investors and their trading behavior. Same findings were suggested by Li and Yu (2012), where the author demonstrates interaction effects between lagged returns and predictability. We expect the coefficient for bad economic times to be positive because the autoregression is stronger during this market state.

3.4 Good and Bad economic states

3.4.1 Expansions and Recessions

The NBER's Business Cycle Dating Committee maintains a chronology of the U.S business cycle. It compromises alternating dates of peaks and troughs in economic activity. They define a recession as a period between a peak and a trough, whereas an expansion occurs between a period when economic activity rises substantially. A recession can last from a few months to more than a year, while an expansion usually lasts for several years. It may occur brief reversals, which means a recession may have a short period of expansion followed by further decline; an expansion may include a short period of recessions followed by further growth. They do not use a fixed definition of economic activity. Instead, they choose to examine and compare the behavior of various measures for the economic activity, like real GDP measured on the product and income sides, economy-wide employment, and real income (NBER, 2010).

Table 3 reports recessions and expansions state in the US over the total sample period from June 1857 to November 2017[10]. According to this data, there were 33 periods of recession and 34 periods of expansion from December 1854 to June 2009. The most

[8] https://schwert.ssb.rochester.edu/mstock.htm

[9] https://www.crsp.com/

[10] https://www.nber.org/cycles/

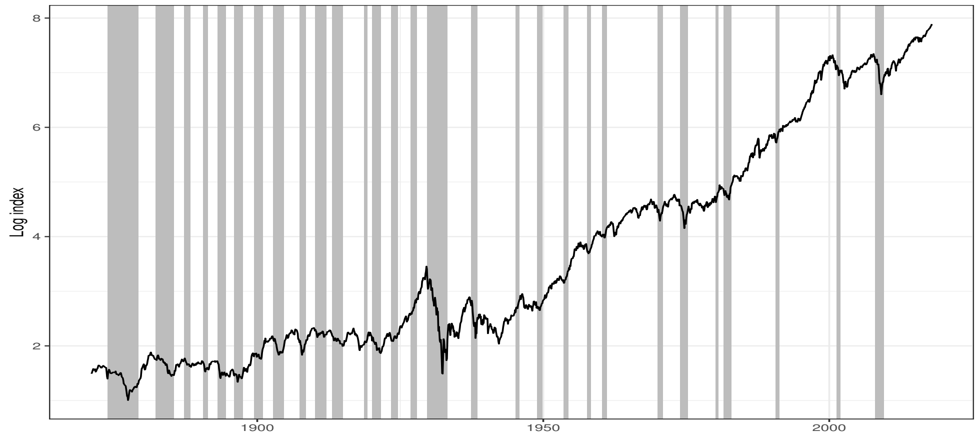
extended recession period was in March 2001, and the shortest in January 1920. It lasted 1278 months in total. On the other hand, the expansion period lasted almost half of the time of the recession period with 693 months. It was longest in June 2009, and shortest in December 1914.

Table 3: Expansions and Recessions data

Recession		**Expansion**	
Dates	Duration	Dates	Duration
		Dec 1854-May 1857	30
Jun 1857-Nov 1858	18	Dec 1858-Sep 1860	22
Oct 1860-May 1861	8	Jun 1861-Mar 1865	46
Apr 1865-Nov 1867	32	Dec 1867-May 1869	18
Jun 1869-Nov 1870	18	Dec 1870-Sep 1873	34
Oct 1873-Feb 1879	65	Mar 1879-Feb 1882	36
Mar 1882-Apr 1885	38	May 1885-Feb 1887	22
Mar 1887-Mar 1888	13	Apr 1888-May 1890	27
Jul 1890-Apr 1891	10	May 1891-Des 1892	20
Jan 1893-May 1894	17	Jun 1894-Nov 1895	18
Dec 1895-May 1897	18	Jun 1897-May 1899	24
Jun 1899-Nov 1900	18	Dec 1900-Aug 1902	21
Sep 1902-Jul 1904	23	Aug 1904-Apr 1907	33
May 1907-May 1908	13	Jun 1908-Des 1909	19
Jan 1910-Des 1911	24	Jan 1912-Des 1912	12
Jan 1913-Nov 1914	23	Dec 1914-Jul 1918	44
Aug 1918-Feb 1919	7	Mar 1919-Des 1919	10
Jan 1920-Jun 1921	18	Jul 1921-Apr 1923	22
May 1923-Jun 1924	14	Jul 1924-Sep 1926	27
Oct 1926-Oct 1927	13	Nov 1927-Jul 1929	21
Aug 1929-Feb 1933	43	Mar 1933-Apr 1937	50
May 1937-May 1938	13	Jun 1938-Jan 1945	80
Feb 1945-Sep 1945	8	Oct 1945-Oct 1948	37
Nov 1948-Sep 1949	11	Oct 1949-May 1953	45
Jul 1953-Apr 1954	10	May 1954-Jul 1957	39
Aug 1957-Mar 1958	8	Apr 1958-Mar 1960	24
Apr 1960-Jan 1961	10	Feb 1961-Nov 1969	106
Dec 1969-Oct 1970	11	Nov 1970 -Oct 1973	36
Nov 1973-Feb 1975	16	Mar 1975-Des 1979	58
Jan 1980-Jun 1980	6	Jul 1980-May 1981	12
Jul 1981-Oct 1982	16	Nov 1982-May 1990	92
Jul 1990-Feb 1991	8	Mar 1991-Feb 2001	120
Mar 2001-Oct 2001	8	Nov 2001-Nov 2007	73
Dec 2007-May 2009	18	Jun 2009-Nov 2017	102

US Business Cycle Recessions and Expansions. The data is provided by National Bureau of Economic Research. Duration is measured in the number of months.

Figure 1: S&P 500 Index - January 1871 to December 2017



Recession and expansion markets over the historical period. Shaded areas indicate recession market phases.

Figure 2: S&P 500 Index - January 1871 to December 1944

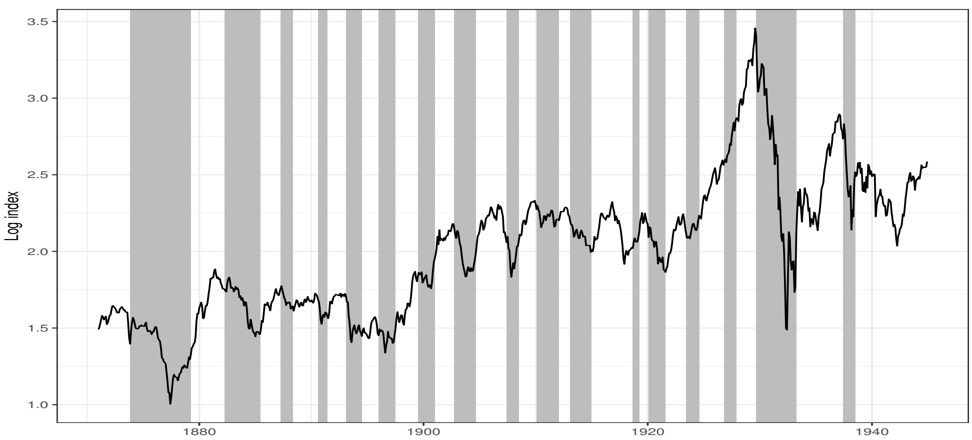


Figure 3: S&P 500 Index - January 1945 to December 2017

Figure 2 and 3 show the expansion and recession markets over the two historical subperiods: 1871-1944 and 1995-2017. Shaded areas indicate recession market phases.

3.4.2 Bull and Bear states

There is no formal definition of bull and bear markets in the finance literature, and therefore, there is no single preferred method to identify the state of the stock market. Financial analysis has a common consensus that a bull market characterizes as a period of generally rising prices, whereas a bear market is a period of falling prices. However, analysts have a different point of view when it comes to the dating of bull and bear markets. In this case, one finds that they are broken up into two distinct groups. According to (Zakamulin,2017,p.183), one group insists that in order to qualify as a bull (bear) market phase, the stock market prices should increase (decrease) substantially. For example, the rise (fall) in the stock market price should be greater than 20% from the previous local trough (peak) in order to qualify for being a distinct bull (bear) market. However, the other group believes that in order to qualify for a bull (bear) name, the stock market price should increase (decrease) over a substantial period. For example, the stock market price should rise (fall) over a period of greater than five months in order to qualify for being a distinct bull (bear) market.

Our data for bull and bear market is from Zakamulin (2017), which have been generated by using a dating algorithm proposed by Pagan and Sossounov (2003) to detect the turning points between the bull and bear markets. They adopted another formal dating method proposed by Bry and Boschan (1971), with some slight modifications to identify turning points in the business cycles.

The algorithm proposed by Pagan and Sossounov (2003) is based on a complex set of rules and consists of two main steps: determination of initial turning points in raw data and censoring operations. Firstly, in order to determine the initial turning points, one has to use a window of length $T_{\text{window}} = 8$ months on either side of the date and identifies a peak (trough) as point higher (lower) than other points in the window. Secondly, one enforces the alternation of turning points by selecting the highest of multiple peaks and lowest of multiple troughs. Censoring operations require that one should eliminate phases less than four months unless changes exceed 20%, and eliminate cycles less than 16 months. A short description of the algorithm of Bry and Boschan (1971) is based on the idea that the trend in the stock market price should continue over a substantial period from the previous peak or trough in order to qualify as a distinct phase.

Table 4: Bull and Bear data

Bull markets			**Bear markets**		
Dates	Duration	Amplitude	Dates	Duration	Amplitude
			Jan 1857-Oct 1857	10	-45
Nov 1857-Mar 1858	5	45	Apr 1858-Jun 1859	15	-15
Jul 1859-Oct 1860	16	57	Nov 1860-May 1861	7	-24
Jun 1861-Mar 1864	34	176	Apr 1864-Mar 1865	12	-26
Apr 1865-Oct 1866	19	18	Nov 1866-Apr 1867	6	-9
May 1867-Aug 1869	28	33	Sep 1869-Dec 1869	4	-1
Jan 1870-Apr 1872	28	21	May 1872-Nov 1873	19	-22
Dec 1873-Apr 1875	17	2	May 1875-Jun 1877	26	-39
Jul 1877-May 1881	47	119	Jun 1881-Jan 1885	44	-35
Feb 1885-Nov 1886	22	33	Dec 1886-Mar 1888	16	-16
Apr 1888-May 1890	26	18	Jun 1890-Jul 1891	14	-18
Aug 1891-Feb 1892	7	7	Mar 1892-Jul 1893	17	-38
Aug 1893-Aug 1895	25	25	Sep 1895-Aug 1896	12	-27
Sep 1896-Aug 1897	12	35	Sep 1897-Apr 1898	8	-7
May 1898-Apr 1899	12	34	May 1899-Jun 1900	14	-9
Jul 1900-Aug 1902	26	52	Sep 1902-Sep 1903	13	-29
Oct 1903-Jan 1906	28	63	Feb 1906-Oct 1907	21	-36
Nov 1907-Sep 1909	23	57	Oct 1909-Jul 1910	10	-18
Aug 1910-Sep 1912	26	13	Oct 1912-Jul 1914	22	-24
Aug 1914-Oct 1916	27	51	Nov 1916-Nov 1917	13	-31
Dec 1917-Oct 1919	23	29	Nov 1919-Aug 1921	22	-22
Sep 1921-Feb 1923	18	33	Mar 1923-Jul 1923	5	-14
Aug 1923-Aug 1929	73	295	Sep 1929-Jun 1932	34	-85
Jul 1932-Jan 1934	19	83	Feb 1934-Mar 1935	14	-21
Apr 1935-Feb 1937	23	95	Mar 1937-Mar 1938	13	-53
Apr 1938-Dec 1938	9	36	Jan 1939-Apr 1942	40	-38
May 1942-Jun 1943	14	52	Jul 1943-Nov 1943	5	-6
Dec 1943-May 1946	30	64	Jun 1946-Feb 1948	21	-24
Mar 1948-Jun 1948	4	11	Jul 1948-Jun 1949	12	-11
Jul 1949-Dec 1952	42	77	Jan 1953-Aug 1953	8	-12
Sep 1953-Jul 1956	35	112	Aug 1956-Dec 1957	17	-16
Jan 1958-Jul 1959	19	45	Aug 1959-Oct 1960	15	-10
Nov 1960-Dec 1961	14	29	Jan 1962-Jun 1962	6	-20
Jul 1962-Jan 1966	43	60	Feb 1966-Sep 1966	8	-16
Oct 1966-Nov 1968	26	35	Dec 1968-Jun 1970	19	-30
Jul 1970-Apr 1971	10	33	May 1971-Nov 1971	7	-6
Dec 1971-Dec 1972	13	16	Jan 1973-Sep 1974	21	-45
Oct 1974-Dec 1976	27	45	Jan 1977-Feb 1978	14	-15
Mar 1978-Nov 1980	33	58	Dec 1980-Jul 1982	20	-21
Aug 1982-Jun 1983	11	41	Jul 1983-May 1984	11	-7
Jun 1984-Aug 1987	39	115	Sep 1987-Nov 1987	3	-28
Dec 1987-May 1990	30	46	Jun 1990-Oct 1990	5	-15
Nov 1990-Jan 1994	39	49	Feb 1994-Jun 1994	5	-5
Jul 1994-Aug 2000	74	231	Sep 2000-Sep 2002	25	-43
Oct 2002-Oct 2007	61	75	Nov 2007-Feb 2009	16	-50
Mar 2009-Apr 2011	26	71	May 2011-Sep 2011	5	-16
Oct 2011-Dec 2017	75	63			

The dates of bull and bear markets over the total sample period from January 1857 to December 2017. Duration is measured in the number of months. Amplitudes are defined as % changes in the stock index prices (not adjusted for dividends).

3.4.3 Investor sentiment

Baker and Wurgler (2007) developed a new investor sentiment approach that is called top-down model. They argued that many of the bottom-up models lead to a similar reduced form of variation over time in mass psychology, and therefore, it is certain that none of the models is uniquely true. Also, they point out that investors and markets behavior is too complicated to be summarized by a few selected biases and trading frictions. Therefore, their new top-down approach focuses on the measurement of reduced-form, aggregate sentiment, and traces its effect to market returns and individual stocks. The new direction in this approach is built on the two broader and more irrefutable assumptions of behavioral finance. These two assumptions involve sentiment and the limits to arbitrage to explain which stocks are likely to be most affected by sentiment, rather than simply pointing out the level of stock prices in the aggregate depend on sentiment. However, variables like stocks of low capitalization, younger, unprofitable, non-dividend paying, high volatility, growth companies, or stock of firms in financial distress are likely to be sensitive to investor sentiment.

Baker and Wurgler (2007) defined the sentiment index by the first principal component of six measures of investor sentiment. This component analysis filters out unsystematic noise in the six measures and focuses on their common component, which is investor sentiment. These six measures are the closed-end fund discount, the number of IPOS, the NYSE share turnover, the equity share in new issues, the average first-day return of IPOs, and the dividend premium. Baker and Wurgler (2007) remove the business cycle information by taking regression of each of the raw sentiment measures on a set of macroeconomic variables, and they use the residuals to develop the sentiment index. We use this sentiment index[11] to generate two dummy variables for good and bad economic states. The first one is defined by detecting whenever the sentiment index is above or below its historical mean. However, Zakamulin (2017) argued that more applicable method is to examine the relative change of the sentiment index. The algorithm to detect whenever the sentiment index is increasing or decreasing is the same as the one used in bull and bear market.

[11] `http://people.stern.nyu.edu/jwurgler/`

Table 5: Sentiment states data

Increasing sentiment			**Decreasing sentiment**		
Dates	Duration	Amplitude	Dates	Duration	Amplitude
Jul 1965-Dec 1969	54	-250	Jan 1970-Dec 1971	24	-143
Jan 1972-Mar 1973	15	-67	Apr 1973-Nov 1974	20	407
Dec 1974-Jul 1975	8	-18	Aug 1975-Nov 1976	16	43
Dec 1976-Sep 1979	34	-94	Oct 1979-Mar 1980	6	32
Apr 1980-Dec 1981	21	-343	Jan 1982-May 1983	17	-123
Jun 1983-Feb 1984	9	-1471	Mar 1984-Apr 1986	26	-79
May 1986-Jan 1987	9	167	Feb 1987-Nov 1988	22	-136
Dec 1988-Apr 1990	17	-156	May 1990-Jan 1991	9	-1050
Feb 1991-Mar 1993	26	-438	Apr 1993-Aug 1993	5	-46
Sep 1993-Dec 1993	4	117	Jan 1994-Jul 1995	19	-103
Aug 1995-Apr 1997	21	9700	May 1997-Dec 1998	20	-123
Jan 1999-Feb 2001	26	-2667	Mar 2001-Aug 2003	30	-127
Sep 2003-Apr 2007	44	-239	May 2007-Apr 2009	24	-245
May 2009-Aug 2009	4	-57	Sep 2009-Mar 2010	7	64
Apr 2010-May 2011	14	-158	Jun 2011-Jun 2012	13	-160
Jul 2012-Oct 2012	4	-360	Nov 2012-Sep 2015	35	120

Table 5 reports increasing and decreasing sentiment states in the US over the total sample period from July 1965 to September 2015. Duration is measured in the number of months, and amplitudes are defined as % change in the sentiment index price from the previous peak or through. The data is from Baker and Wurgler (2007)

Figure 4: Sentiment Index - increasing and decreasing sentiment

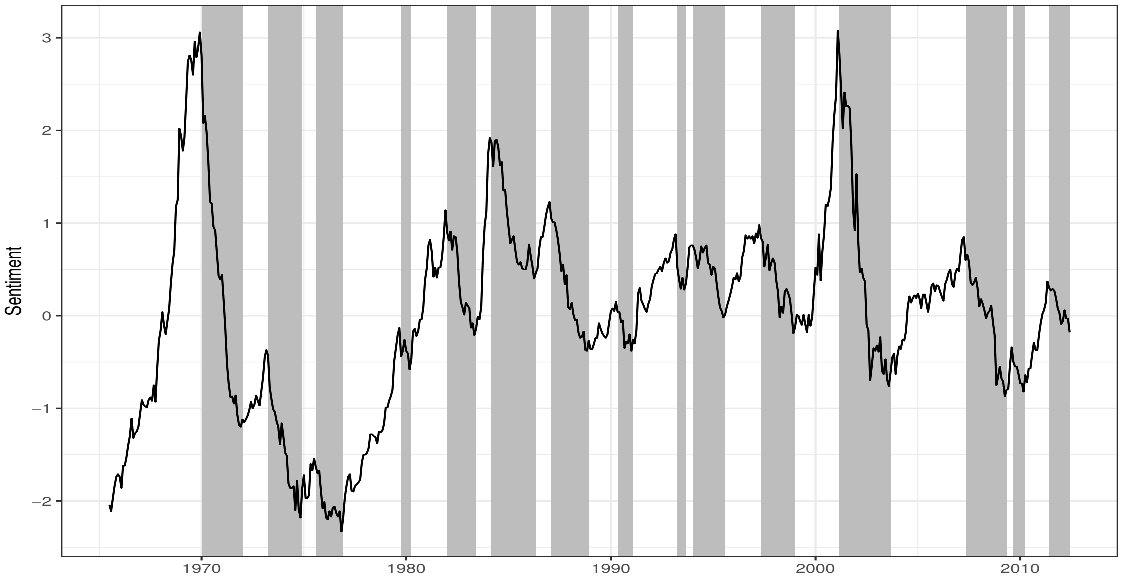


Figure 5: Sentiment Index - bull and bear states

Figure 4 and 5 show the sentiment stages from July 1965 to September 2015. After 1961 which defines the period for the crash of growth stocks, the investor sentiment was low from this point. Followed to a subsequent peak in 1968 and following with an electronic bubble in 1969. It fell once again by the mid- 1970s, but it picked itself up and reached a peak in the late 1970s because of the biotech bubble. After that, it dropped in the late 1980s, but it started to rise in the early 1990s and reached a peak in the Internet bubble. The late 1960s, early and mid-1980s, mid-1990 and the begin of 2000 are periods of high-sentiment. Also, the sentiment index has been almost constant in the recent decade.

4 Methodology

4.1 Predictive regression

The basic linear predictive regression model for stock return is modeled as:

$$r_t = \alpha + \beta X_{t-1} + \epsilon_t, \tag{5}$$

where r_t is the stock return in month t, α is a constant, β is a slope of the regression line, X_{t-1} is the predictor of stock returns at month $t-1$ and ϵ_t is the error term.

We are using macroeconomic and technical predictors for the regression analysis to examine whether there exists significant evidence of predicting the stock return in different economic states. The alternative predictive regression for the two-state model is computed as:

$$r_t = \alpha + \beta_{good} \cdot (1 - I_{bad,t-1}) \cdot X_{t-1} + \beta_{bad} \cdot I_{bad,t-1} \cdot X_{t-1} + \epsilon_t, \tag{6}$$

where $I_{bad,t\text{-}1}$ is a dummy variable equal to 1 in the bad economic state and 0 otherwise. These dummy variables are calculated from the previous period $t-1$. One needs to estimate regressions (5) and (6) and see the difference, whether β_{good} and β_{bad} are statistically significant, and whether $\overline{R}^2$ is higher.

When the past monthly return is used as a predictor, the regression is called the autoregression model of order 1, and in the one-state model it is computed as:

$$r_t = \alpha + \beta r_{t-1} + \epsilon_t, \tag{7}$$

moreover, in the two-state market:

$$r_t = \alpha + \beta_{good} \cdot (1 - I_{bad,t-1}) \cdot r_{t-1} + \beta_{bad} \cdot I_{bad,t-1} \cdot r_{t-1} + \epsilon_t. \tag{8}$$

4.2 Newey–West estimator

Most of the macroeconomic and technical predictors are persistent variables. Hence, we expect the ϵ_t exhibits serial dependency. Therefore, one needs a particular method for computing standard errors. We are using a Newey-West estimator that is controlling for heteroskedasticity and autocorrelation, which is derived from Newey and West (1987). Geweke (1981) pointed out that by using multi-month lagged returns to predict future returns can increase statistical power. One is required to set a maximum lag order of autocorrelation to compute a Newey-West estimator. It can be challenging to find an optimal lag length in a time series, because there exist several criteria for different techniques, depending on the model one wants to use. The frequency spectrum of the time series and the sampling rate are two crucial factors to look into when choosing the optimal lag length. We are using Newey-West t-statistics with a 12-month lag for all the regression since we are using monthly data.

One wants to test the hypothesis for the significance of a single regression coefficient. Equation (9) is a t-statistics where the standard errors are measured by Newey-West estimator. It is computed by the following equation:

$$t = \frac{\widehat{\beta}_i - \beta_i^*}{SE^{\text{Newey}}(\beta)}. \tag{9}$$

We are testing the null hypothesis H_0:$\beta_i = 0$ against the alternative hypothesis H_1:$\beta_i \neq 0$ for i = 0,1,2,... for significant level of 1%, 5% and 10%. If the probability value for the Newey West t-statistics for the given regressor is less than the significant level, there is evidence of a variation in predictors will have a significant effect on the stock return, given that all other factors are constant.

4.3 R-squared

According to Verbeek (2008), the R-squared (R^2) is a statistic that explains the goodness of fit of a model. This statistical measure shows the proportion of the (sample) variance of the dependent variable (r_t) that is explained by the independent variable (X_{t-1}). R-squared ranges between value 0 and 1, where 1 indicates that the regression predictions perfectly fit the data.

The adjusted R-squared is a modified version of R-squared that has been adjusted for the number of predictors in the model. It only increases when including new independent variable explain more than what one would expect by chance, which penalizes the use of unnecessary variables in the model. We are only using adjusted R-squared as a measurement to compare the goodness of fit for one-state and two-state models. The R-squared is computed as:

$$R^2 = 1 - \frac{SS_{\text{res}}}{SS_{\text{tot}}}, \tag{10}$$

moreover, the adjusted R-squared:

$$\overline{R}^2 = 1 - (1 - R^2) \left[\frac{n-1}{n-p-1} \right], \tag{11}$$

where SS_{res} is the sum of squares of residuals, SS_{tot} is the total sum of squares that explain the proportional to the variance of the data, n is sample size, and p is the number of predictors.

5 Empirical results

In this section, we present the results of our analysis conducted using the methods previously described. We evaluate the in-sample goodness of fit and statistical significance of the coefficient for predictors of stock return in a given market state. The data starts from January 1871 to December 2017 with a window length of 1764 months. However, some of the data for macroeconomic variables, technical indicators, and investor sentiment were not available from the beginning; we included the exact length of analysis in our tables. The sentiment data has a shorter sample period that starts from July 1965 to September 2015 with a window length of 603 months. The one-state and two-state regression models estimate the predictability of the stock return that is presented in Tables 6-9. Each table reports the estimator of β coefficient respectively to the market state (β_{good} and β_{bad}), the corresponding probability value of the Newey-West t-statistics (P$>|t|$), the adjusted R-squared ($\overline{R}^2$) and the change in the adjusted R-squared ($\Delta\overline{R}^2$) between one- and two-state regression models.

The results of the one-state predictive regression serve as a benchmark for the comparison of the two-state model. For the one-state model, only earnings-to-price ratio and long-term return has shown significant performance in predicting the stock market returns at 5% level or stronger, with an $\overline{R}^2$ of 0.19% and 0.11%. Their beta coefficients are 0.01 and 0.10, respectively. However, we do not find any significant evidence of predictability by using technical indicators.

5.1 Expansions and Recessions

The two-state regression model of recessions and expansions is shown in Table 6. By analyzing macroeconomic variables, we observe that five variables are significant in predicting the stock returns good economic times, and seven variables are significant in bad economic times at 10% level or stronger. Only dividend-to-price and earnings-to-price were significant in both market states at 5% level or stronger. Also, the adjusted R-squared has also improved in the two-state regression model for every macroeconomic variable, ranging from 0.01% for the long-term return to 1.7% for the dividend-price ratio.

In the absence of technical variables, MOM(12) and SMA(10) are significant in predicting the stock return in good economic states, on 5% and 10%, respectively. However, in bad economic times, only a conditional variance was significant on 1%. The change in adjusted R-squared ranged between -0.06% for MOM(12) and SMA(10) to 1.85% for a conditional variance.

5.2 Bull and Bear states

The two-state regression model of a bull and bear market is shown in Table 7. By analyzing macroeconomic variables, we observe that most of the variables are significant in predicting the stock returns both in bull and bear markets on 5% level or stronger. The long-term return is the only variable that does not predict in both market states. Almost all variables that are significant in good economic times have a positive and higher beta coefficient, whereas dividend-to-price ratio and default return spread have a negative and lower coefficient. They are significant at 1% and 5% level, respectively. However, eight variables that are significant in bad economic times have negative and lower beta coefficients. The adjusted R-squared has also improved for every variable in the two-state regression model.

In contrast to macroeconomic variables, there is only one technical predictor that is significant in predicting the stock return in both bull and bear markets, which is conditional variance. It is significant at 1% in both markets, but the beta coefficient is positive in periods of a bull market and negative in a bear market. Past monthly return and SMA(10) are significant at 10% and 5% in bear markets with positive beta coefficients. The adjusted R-squared is also higher for all technical variables.

5.3 Investor sentiment

The two-state regression model of high and low investor sentiment index is shown in Table 8. When analyzing macroeconomic variables, we observe that only the long-term return is significant at the 5% in times where investor sentiment is below the historical mean, with a positive beta coefficient, and an adjusted R-squared of 0.61%. None of the macroeconomic variables have shown significance in times where investor sentiment is above the historical mean.

In the absence of technical variables, a conditional variance is the only indicator that is significant. In the periods of high sentiment, it is significanc at 1%, and 5% in periods of low sentiment. It has a negative beta coefficient in both market states. The adjusted R-squared has decreased for almost every macroeconomic and technical predictor, with the exception of long-term return and conditional variance.

Table 9 reports the two-state regression model of increasing and decreasing investor sentiment index. We observe some slight adjustment in the predictability of the macroeconomic variables. The Term spread is the only macroeconomic variables that have shown significant predictability in times of increasing investor sentiment. It is significant at the 10% with a coefficient of 0.23 and an adjusted R-square of 0.08. In the times of decreasing investor sentiment, only long-term return and default return spread are significant at 5% and 1% level, with coefficients of 0.22 and 0.1, and adjusted R-square of 1% and 0.1%, respectively.

Conditional variance is the only technical variable which is significant in decreasing sentiment index at 1% with a negative beta coefficient, and none were significant when investor sentiment index was increasing. Compared to the previous model of high and low sentiment, the adjusted R-squared has slightly increased for most of the technical variables, with the exception of past monthly return.

Table 6: Results of the expansions and recessions

Macroeconomic predictor variables	Data	One-state regression β	$P>\|t\|$	$\overline{R}^2$	Two-state regression β_{good}	$P>\|t\|$	β_{bad}	$P>\|t\|$	$\overline{R}^2$	Imp $\Delta\overline{R}^2$
Dividend-price ratio	1871-2017	0.002	44.2	-0.01	0.008	1.4**	0.011	0.2***	1.69	1.70
Earnings-price ratio	1871-2017	0.010	7.8*	0.19	0.009	4.1**	0.011	1.1**	1.75	1.56
Dividend-earnings ratio	1871-2017	-0.005	42.4	0.03	-0.006	27.0	0.007	42.9	0.34	0.31
Book-to-market ratio	1921-2017	0.010	23.2	0.15	0.021	4.8**	0.002	86.1	1.01	0.86
Net equity expansions	1926-2017	-0.138	12.0	0.34	-0.014	89.6	-0.221	4.0**	0.56	0.22
T-bill rate	1920-2017	-0.009	86.2	-0.08	0.053	34.2	-0.145	4.7**	0.38	0.46
Long-term yield	1919-2017	0.006	91.9	-0.08	0.057	33.0	-0.142	9.0*	0.61	0.69
Long-term return	1926-2017	0.100	5.8*	0.11	0.055	35.3	0.203	7.3*	0.12	0.01
Term spread	1920-2017	0.073	52.7	-0.05	0.146	18.6	-0.398	25.5	0.61	0.66
Default yield spread	1919-2017	0.044	93.0	-0.08	0.988	7.5*	-0.263	58.5	1.91	1.99
Default return spread	1926-2017	0.038	36.4	-0.03	-0.022	63.3	0.218	0.0***	0.97	1.00
Inflation	1913-2017	-0.219	41.5	-0.01	-0.461	9.7*	0.212	65.7	0.08	0.09
Technical predictor variables										
past monthly return	1871-2017	0.070	11.7	0.44	0.025	50.9	0.124	10.6	0.62	0.18
Conditional variance	1885-2017	-0.368	56.4	0.06	1.421	25.6	-1.260	0.7***	1.91	1.85
MOM(12)	1871-2017	0.014	17.4	0.22	0.016	3.7**	0.011	62.8	0.16	-0.06
SMA(10)	1871-2017	0.002	16.9	0.16	0.002	9.5*	0.002	52.5	0.10	-0.06

This table reports the results of a one-state and two-state predictive models. The market is indicated *good* and *bad* using NBER recessions and expansions cycles. The market states indicate I_{bad} recession and I_{good} otherwise. We included predictor variables, time period, β coefficient, the p-value for t-statistics, adjusted R-squared, and differences in adjusted R-squared between one-state and two-state regression model. All p-values are evaluated using the Newey-West procedure controlling for heteroskedasticity and autocorrelation. Predicting variables denoted with ***, ** and * are significant on 1%, 5% and 10% levels, respectively.

Table 7: Results of the bull and bear states

Macroeconomic predictor variables	Data	One-state regression β	P>$\|t\|$	$\overline{R}^2$	Two-state regression β_{good}	P>$\|t\|$	β_{bad}	P>$\|t\|$	$\overline{R}^2$	Imp $\Delta\overline{R}^2$
Dividend-price ratio	1871-2017	0.002	44.2	-0.01	0.009	0.1***	0.016	0.0***	15.24	15.25
Earnings-price ratio	1871-2017	0.010	7.8*	0.19	0.009	0.4***	0.017	0.0***	15.46	15.27
Dividend-earnings ratio	1871-2017	-0.005	42.4	0.03	-0.014	2.3**	0.038	0.0***	8.46	8.43
Book-to-market ratio	1921-2017	0.010	23.2	0.15	0.044	0.0***	-0.026	0.0***	15.26	15.11
Net equity expansions	1926-2017	-0.138	12.0	0.34	0.280	1.3**	-0.401	0.2***	3.88	3.54
T-bill rate	1920-2017	-0.009	86.2	-0.08	0.282	0.0***	-0.344	0.0***	6.59	6.67
Long-term yield	1919-2017	0.006	91.9	-0.08	0.254	0.0***	-0.392	0.0***	10.56	10.64
Long-term return	1926-2017	0.100	5.8*	0.11	0.251	0.1***	-0.185	17.0	0.91	0.80
Term spread	1920-2017	0.073	52.7	-0.05	0.579	0.0***	-1.253	0.0***	10.17	10.22
Default yield spread	1919-2017	0.044	93.0	-0.08	1.977	0.0***	-1.478	0.0***	18.64	18.72
Default return spread	1926-2017	0.038	36.4	-0.03	-0.186	0.1***	0.339	0.0***	7.30	7.33
Inflation	1913-2017	-0.219	41.5	-0.01	0.771	1.9**	-0.976	1.8**	1.25	1.26
Technical predictor variables										
Past monthly return	1871-2017	0.070	11.7	0.44	0.040	45.3	0.111	9.5*	0.49	0.05
Conditional variance	1885-2017	-0.368	56.4	0.06	3.497	0.1***	-2.554	0.0***	10.07	10.01
MOM(12)	1871-2017	0.014	17.4	0.22	-0.002	89.8	0.041	15.0	0.77	0.55
SMA(10)	1871-2017	0.002	16.9	0.16	-0.003	43.9	0.009	2.8**	1.29	1.13

This table reports the results one-state of two-state predictive models. The market is indicated *good* and *bad* using Zakamulin (2017) definition of bull and bear market. The market states indicate I_{bad} bear market and I_{good} otherwise. We included predictor variables, time period, β coefficient, the p-value for t-statistics, adjusted R-squared, and differences in adjusted R-squared between one-state and two-state regression model. All p-values are evaluated using the Newey-West procedure controlling for heteroskedasticity and autocorrelation. Predicting variables denoted with ***, ** and * are significant on 1%, 5% and 10% levels, respectively.

Table 8: Results of the high and low sentiment

Macroeconomic predictor variables	Data	One-state regression β	P>$\lvert t \rvert$	$\overline{R}^2$	Two-state regression β_{good}	P>$\lvert t \rvert$	β_{bad}	P>$\lvert t \rvert$	$\overline{R}^2$	Imp $\Delta\overline{R}^2$
Dividend-price ratio	196507-201509	0.004	42.3	-0.01	0.006	21.0	0.006	21.1	-0.05	-0.04
Earnings-price ratio	196507-201509	0.007	7.8*	0.04	0.004	42.3	0.004	43.6	-0.13	-0.17
Dividend-earnings ratio	196507-201509	0.006	84.7	-0.16	0.000	96.3	0.001	89.6	-0.33	-0.17
Book-to-market ratio	196507-201509	0.003	58.4	-0.10	0.004	68.0	0.003	66.0	-0.29	-0.19
Net equity expansions	196507-201509	2.579	6.6*	0.34	-0.090	50.3	0.029	90.3	-0.21	-0.55
T-bill rate	196507-201509	-0.045	76.2	-0.08	-0.025	69.0	-0.019	78.6	-0.30	-0.22
Long-term yield	196507-201509	-0.014	79.6	-0.08	0.012	85.9	0.019	79.7	-0.32	-0.24
Long-term return	196507-201509	0.025	71.4	0.11	0.117	11.7	0.162	1.5**	0.61	0.5
Term spread	196507-201509	0.137	23.2	-0.05	0.139	29.3	0.144	31.1	-0.09	-0.04
Default yield spread	196507-201509	0.539	16.8	0.15	0.434	46.6	0.533	42.5	-0.06	-0.21
Default return spread	196507-201509	0.539	36.3	0.24	0.072	12.8	0.075	12.9	0.12	-0.12
Inflation	196507-201509	-0.611	33.4*	0.01	-1.151	11.6	-0.451	53.5	0.13	0.12
Technical predictor variables										
Past monthly return	196507-201509	0.035	46.9	-0.04	-0.028	62.7	-0.039	32.4	-0.22	-0.18
Conditional variance	196507-201509	-1.074	0.2***	1.12	-1.080	0.1***	-1.229	2.3**	1.15	0.03
MOM(12)	196507-201509	0.007	61.1	-0.10	0.009	64.7	0.009	58.7	-0.23	-0.13
SMA(10)	196507-201509	0.001	61.3	-0.11	0.000	97.8	0.003	38.4	-0.16	-0.05

This table reports the results of one-state and two-state predictive models. The market is indicated *good* and *bad* using investor sentiment. The market states indicate I_{bad} when investor sentiment is over historical mean and I_{good} otherwise. We included predictor variables, time period, β coefficient, the p-value for t-statistics, adjusted R-squared, and differences in adjusted R-squared between one-state and two-state regression model. All p-values are evaluated using the Newey-West procedure controlling for heteroskedasticity and autocorrelation. Predicting variables denoted with ***, ** and * are significant on 1%, 5% and 10% levels, respectively.

Table 9: Results of the increasing and decreasing sentiment

Macroeconomic predictor variables	Data	One-state regression β	P>$\|t\|$	$\overline{R}^2$	Two-state regression β_{good}	P>$\|t\|$	β_{bad}	P>$\|t\|$	$\overline{R}^2$	Imp $\Delta\overline{R}^2$
Dividend-price ratio	196507-201509	0.004	42.3	-0.01	0.005	23.0	0.006	20.8	0.00	-0.01
Earnings-price ratio	196507-201509	0.007	7.8*	0.04	0.004	45.5	0.004	41.5	-0.08	-0.12
Dividend-earnings ratio	196507-201509	0.006	84.7	-0.16	0.000	97.4	0.001	84.8	-0.32	-0.16
Book-to-market ratio	196507-201509	0.003	58.4	-0.10	0.004	64.8	0.003	71.4	-0.29	-0.19
Net equity expansions	196507-201509	2.579	6.6*	0.34	-0.153	17.8	0.053	80.4	-0.03	-0.37
T-bill rate	196507-201509	-0.045	76.2	-0.08	-0.023	70.0	-0.021	76.4	-0.31	-0.23
Long-term yield	196507-201509	-0.014	79.6	-0.08	0.021	77.6	0.008	90.8	-0.31	-0.23
Long-term return	196507-201509	0.025	71.4	0.11	0.012	88.7	0.220	0.1***	1.11	1.00
Term spread	196507-201509	0.137	23.2	-0.05	0.228	4.1*	0.077	62.1	0.08	0.13
Default yield spread	196507-201509	0.539	16.8	0.15	0.767	22.5	0.452	46.1	0.08	-0.07
Default return spread	196507-201509	0.539	36.3	0.24	0.044	34.3	0.098	4.3**	0.33	0.09
Inflation	196507-201509	-0.611	33.4*	0.01	-0.557	39.6	-0.779	36.1	0.00	-0.01
Technical predictor variables										
Past monthly return	196507-201509	0.035	46.9	-0.04	-0.029	51.9	-0.036	47.8	-0.22	-0.18
Conditional variance	196507-201509	-1.074	0.2***	1.12	0.495	79.7	-1.172	0.0***	1.32	0.20
MOM(12)	196507-201509	0.007	61.1	-0.10	-0.022	24.3	0.025	15.3	0.50	0.60
SMA(10)	196507-201509	0.001	61.3	-0.11	-0.003	29.4	0.004	19.7	0.22	0.33

This table reports the results of one- and two-state predictive regression models. The market is indicated *good* and *bad* using investor sentiment. The market states indicate I_{bad} when investor sentiment is falling and I_{good} otherwise. We included predictor variables, time period, β coefficient, the p-value for t-statistics, adjusted R-squared, and differences in adjusted R-squared between one-state and two-state regression model. All p-values are evaluated using the Newey-West procedure controlling for heteroskedasticity and autocorrelation. Predicting variables denoted with ***, ** and * are significant on 1%, 5% and 10% levels, respectively.

5.4 Robustness tests

To check the robustness in our results, we split a sample into two equal subperiods and estimate regressions for each part. We would like to see whether the results for the entire dataset still apply in these subperiods. If there is no evidence of robustness in the results, then one should further investigate the deviation in each period. Perhaps there was a change in some rules and regulations, a financial crisis or other events that might have caused the findings to be inconsistent. The two subperiods for NBER's chronology of recessions and expansions, and bull and bear markets are divided into January 1871 to December 1943, and January 1944 to December 2017, respectively. The data of investor sentiment has a shorter time period, and therefore, the first period starts from July 1965 to July 1990, whereas the second period begins in August 1990 to September 2015. The robustness tests are shown in Tables 10-13, which can be found in appendices.

5.4.1 Expansions and Recessions

The robustness test of the expansions and recessions is shown in Table 10. For the first subperiod, two out of 12 macroeconomic variables are significant in predicting the stock returns both in good and bad economic states. Those are earnings-to-price ratio and book-to-market with positive beta coefficients. The earnings-to-price ratio is significant at the 10% in periods of expansions and 5% in periods of recessions, whereas book-to-market is significant at 1% and 5% level. However, net equity expansions is only significant at the 5% level in bad economic times with a negative beta coefficient.

In contrast to macroeconomic variables, there are three technical predictors that are significant in predicting the stock return in good economic states, whereas none is significant in bad economic states. A conditional variance, MOM(12) and SMA(10) are significant at 1% and 5% level.

For the second subperiod, the dividend-to-price is the only macroeconomic predictor that is significant in both good and bad economic states. It is significant at the 5% in periods of expansions and 1% in periods of recessions with positive beta coefficients. On the other hand, net equity expansions, long-term return, and default return spread are significant at the 5% in bad economic states with positive beta coefficients.

When it comes to technical indicators, a conditional variance is significance at the

10% in recessions and 1% in expansions with negative beta coefficients. Past monthly return and SMA(10) are significant at 5% and 10% with positive beta coefficients in expansions states.

5.4.2 Bull and bear market states

The robustness test of the bull and bear markets is shown in Table 11. For the first subperiod, eight macroeconomic variables are significant in predicting the stock returns both in bull and bear markets. Dividend-to-price ratio and book-to-market are the only variables that are significant in both market states. They have positive beta coefficients, but the former is significant at the 10% in a bear market, whereas the latter is significant at 1% in a bull market. Almost every variable that is significant at 1% and 5% level in a bull market have a positive beta coefficient, and the large percentage of those variables that are significant at 1% and 10% level in a bear market have a negative beta coefficient. When it comes to technical indicators, only a conditional variance is significant at the 1% level in both market states with a positive beta coefficient in bull and a negative value in bear. Past monthly return is significant at the 10% in a bull market with a positive beta coefficient.

For the second subperiod, seven macroeconomic variables are significant in both bull and bear markets. The long-term return and inflation are significant in either of the market states. The long-term return is significant at the 10% in a bull market with positive beta coefficients, whereas inflation is significant at the 1% level in a bear market with a negative beta coefficient. Like the first subperiod, almost every variable that is significant at 1% and 10% level in a bull market have a positive beta coefficient, except for default return spread. On the other hand, the most of variables that are significant at 1% and 5% level in a bear market have a negative beta coefficient.

However, two technical predictors are significant in both market states. A conditional variance and past monthly return are significant at the 1% in bull and bear. The former has a positive beta coefficient in a bull market, and negative in a bear market. The latter has the opposite signs. Lastly, SMA(10) is significant at the 10% in a bear market with a positive beta coefficient.

5.4.3 Investor sentiment

The robustness test of the high and low sentiment is shown in Table 12. For the first subperiod, three macroeconomic variables are significant in predicting the stock returns in both market states. The dividend-price ratio and default yield spread are significant at 5% and 1% level with positive beta coefficients, whereas inflation is significant at 1% and 5% level with negative beta coefficients. Net equity expansions and long-term return are significant in either good or bad economic states. The first variable is significant at the 5% level in periods of good economic states with a negative beta coefficient. The second variable is significant at the 10% in periods of bad economic states with a positive beta coefficient. In contrast to macroeconomic variables, one technical indicator is significant in periods of high sentiment. A conditional variance is significance at the 10% with a negative beta coefficient.

For the second subperiod, only the default yield spread is significant at the 10% level with negative beta coefficients in good and bad economic states. Net equity expansions is significant at the 5% with a positive coefficient in periods of bad economic states. For the technical indicators, we do observe that conditional variance is significant at the 1% with a negative beta coefficient in periods of low sentiment.

The robustness test of the increasing and decreasing sentiment is shown in Table 13. For the first subperiod, two macroeconomic variables are significant in predicting the stock return in both market states. The dividend-to-price ratio is significant at 5% with a positive beta coefficient in good and bad economic states, which is the same as in high and low sentiment. However, the default yield spread is significant at 5% and 1%, respectively. Net equity expansions, long-term return, default return spread, and inflation are significant in either good or bad economic states. The first variable is significant at 5% in periods of increasing sentiment with a negative beta coefficient, and the last three variables are significant at 1%, 5% and 10% in periods of decreasing sentiment. Inflation is the only variable with a negative beta coefficient. None of the technical indicators are significant.

For the second subperiod, none of the macroeconomic variables are significant in both market states. Net equity expansions is significant at the 10% level in bad economic states with a positive beta coefficient. On the contrary to the first subperiod, conditional variance and MOM(12) are significant at 1% and 10% in periods of decreasing sentiment.

6 Discussion

Firstly, the results of one-state regression model for in-sample prediction are very weak. Only two out of 12 macroeconomic variables are significant at the 10% level. These findings are similar to Welch and Goyal (2008), who stated that most of the macroeconomic variables seems to be unstable and are no longer significant in an in-sample forecast.

Secondly, the two-state regression model for NBER chronology of recessions and expansions has shown that a whole eight out of 12 macroeconomic variables are significant at 10% level or stronger in periods of recessions, whereas only five out of 12 are significant at 5% and 10% levels in periods of expansions. The proportion of the variance in the stock return that is predictable from the macroeconomic variables and technical indicators is slightly higher in the two-state regression model. By comparing our findings to previous studies, we do find some similarities. For instance, Rapach et al. (2010) and Dangl and Halling (2012) find evidence that return predictability appears during recessions as well as during expansions, but the evidence is much stronger during recessions. In addition, predictability increases during bad economic states and decreases during good economic states.

On the other hand, our empirical results are, in some way, contradicting to other findings. For instance, Henkel et al. (2011) do not find evidence that in-sample predictability is the case during expansions, whereas our study finds that only four out of 12 are significant. The main difference is that they reexamined the predictability using a framework of regime-switching vector autoregression (RSVAR) that can match the time-varying dynamics of predictors to the dynamics of expected returns. Additionally, Henkel et al. (2011) chose to forward their attention towards international data samples of G7 countries; this dataset consist of country index returns from the time period of 1973 to 2007. Similarly, Dangl and Halling (2012) also focus their attention on roughly the same time period, from May 1973 to December 2008, attempting to analyze the monthly total excess returns of the S&P 500 index. A noticeable difference between the aforementioned studies and ours, is thereby that our study additionally includes most of the downturns in the US economy before 1950, whereas the others have chosen to exclude periods in time involving some of the major economic crisis. We think it is important that studies should include these major economic crises in order to identify whether there is a trend in bad economic times.

Another interesting observation is that our results are contradicting to Neely et al. (2014). They stated that technical indicators displayed statistical significance in-sample forecasting power that is matching or exceeding that of macroeconomic variables. Furthermore, there is evidence that these two types of indicators provide complementary information over the business cycles. This was quoted as follows; "Technical indicators better detect the typical decline in the equity risk premium near business cycle-peaks, while macroeconomic variables more readily pick up the typical rise in the equity risk premium near cyclical throughs" (Neely,2014,p.2). Our study finds the opposite effect on expansions and recessions. Technical indicators that are significant in periods of recessions have positive beta coefficients, whereas four out of eight macroeconomic variables that are significant in bad economic times have negative beta coefficients.

The results from bull and bear markets show significant evidence of the coefficients for most of the macroeconomic variables and some of the technical indicators. The adjusted R-squared has shown improvement for many predictors in the two-state compared to the one-state regression model. An interesting discovery is that those variables that are significant in a bull market have positive beta coefficients, and those that are significant in a bear market have the opposite sign. The bull and bear markets appear to be a more suitable and advantageous measure of the market states as it is identified with a shorter delay compared to expansions and recessions, which are dated after one to two years.

Lastly, the results from investor sentiment have been disappointing. According to Diether et al. (2002) and Tetlock (2007), the disagreement amongst investor and their reactions to the news seems to predict future returns. Further, Patton and Timmermann (2010) pointed out that polarization of opinions may produce a spike in disagreement, which causes return predictability to be concentrated in bad economic times. They emphasized that the effect of investor sentiment can skew rational behavior and make for overly optimistic or pessimistic choices. However, we do not have enough evidence in our results to confirm these claims. An implication with investor sentiment data is due to the fact that it has a shorter sample period compared to expansions and recessions, and bull and bear markets. This leads to an unrealistic comparison of the results. In addition,

Figure 5 shows that investor sentiment has barely moved from the historical mean in the last ten years. These arguments might be the reasons why we did not receive more significant results for investor sentiment.

7 Conclusion

Our thesis systematically investigates the in-sample performance of linear regressions that predict the stock return with macroeconomic and technical variables. These variables have been considered to be good indicators of the stock returns from previous academic research. In the last two decades, many researchers have proposed that information about the past market state can influence stock return predictability. We examined these claims by including four different definitions of the market state in the analysis.

We tried to replicate methods used by Welch and Goyal (2008) and Huang et al. (2014) and estimated the one-state and two-state predictive regressions to see the differences, whether β_{good} and β_{bad} are statistically significant, and whether $\overline{R}^2$ is higher. Firstly, some of the empirical results are similar to Welch and Goyal (2008) for the one-state model where most of the predictors are unstable and spurious; only two out of 16 variables are significance at the 10% level. Secondly, the two-state model showed mixed performance across the different macroeconomic variables and technical indicators. NBER chronology of recession and expansions performed better in most cases; seven out of 16 variables are significant in good economic states, and eight out of 16 in bad economic states. The goodness of fit was also improved for almost every variable that we have tested. However, most of the predictors performed better in bull and bear markets, where the vast majority have shown improved goodness of fit; most of the insignificant variables in one-state became significant in the two-state model. Also, despite the popularity of Baker and Wurgler (2006) definition of investor sentiment, we were unsuccessful in identifying any improvement for both of our methods used. There might be some implications with investor sentiment index since human psychology is difficult to observe.

Lastly, Welch and Goyal (2008) argued that the predictability of different predictors had been diminished, and their evidence suggested that most of the models are unstable in the last four decades. We tried to examine this phenomenon by conducting the robustness test. For simplicity, we divided data into two equal subperiods and compared the results.

However, our robustness test for the two-state models did not show convincing differences in the subperiods.

There are several subjects that are of interest for future research. One could apply the two-state regression model to other markets, such as commodity and currency markets, to see whether these markets are affected by the different business cycles in the economy as in the stock market. In addition, one could analyze the effect of more unusual underlying variables, applying different time horizons and implement other models to characterize economic market states. Finally, the effect of changes in beta coefficients are relevant and an interesting topic considered from a macroeconomic perspective.

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Appendices

Table 10: Robustness test of the expansions and recessions

Macroeconomic	First period						Second period						Imp
predictor variables	Data	β_{good}	P>$\|t\|$	β_{bad}	P>$\|t\|$	$\overline{R}^2$	Data	β_{good}	P>$\|t\|$	β_{bad}	P>$\|t\|$	$\overline{R}^2$	$\Delta\overline{R}^2$
Dividend-price ratio	1871-1934	0.015	18.6	0.019	11.7	2.27	1944-2017	0.008	2.0**	0.009	0.9***	0.84	-1.43
Earnings-price ratio	1871-1934	0.016	7.3*	0.019	3.8**	2.60	1944-2017	0.005	21.8	0.007	13.5	0.54	-2.06
Dividend-earnings ratio	1871-1934	-0.018	18.7	0.000	99.1	0.48	1944-2017	-0.001	90.0	0.010	13.1	0.24	-0.24
Book-to-market ratio	1921-1968	0.037	0.9***	0.024	4.4**	0.83	1969-2017	0.005	51.5	0.000	99.4	-0.25	-1.08
Net equity expansions	1926-1966	0.026	87.5	-0.256	1.4**	0.96	1967-2017	-0.147	15.9	0.466	3.6**	0.77	-0.19
T-bill rate	1920-1969	0.139	40.2	0.229	28.6	0.17	1970-2017	-0.011	85.0	-0.059	41.6	-0.22	-0.39
Long-term yield	1919-1969	0.106	70.9	-0.163	57.4	0.12	1970-2017	0.021	76.0	-0.033	66.1	-0.21	-0.33
Long-term return	1926-1966	0.024	91.6	0.061	83.5	-0.36	1967-2017	0.039	58.9	0.278	1.1	0.85	1.21
Term spread	1920-1969	0.024	93.2	-0.391	28.2	-0.09	1970-2017	0.163	19.2	0.022	92.6	-0.03	0.06
Default yield spread	1919-1969	0.457	24.4	-0.195	51.3	0.26	1970-2017	0.897	9.1*	0.349	39.0	0.17	-0.09
Default return spread	1926-1966	0.021	88.5	0.296	14.1	0.11	1967-2017	0.025	60.4	0.151	1.8**	0.67	0.56
Inflation	1913-1972	-0.465	19.3	0.451	37.0	0.07	1973-2017	-0.780	16.0	-0.318	64.6	0.00	-0.07
Technical variables													
Past monthly return	1871-1934	0.066	26.5	0.105	28.1	0.57	1944-2017	-0.023	60.2	0.190	2.4**	0.81	0.24
Conditional variance	1885-1950	2.096	0.3***	-0.415	30.2	1.10	1951-2017	-0.845	8.4*	-1.552	0.2***	1.27	0.17
MOM(12)	1871-1934	0.027	0.9***	0.004	87.7	0.28	1944-2017	-0.001	94.7	0.032	20.6	0.11	-0.17
SMA(10)	1871-1934	0.005	3.2**	0.000	91.4	0.16	1944-2017	-0.001	77.1	0.007	7.3*	0.30	0.14

This table reports the robustness test of two-state predictive regression model by splitting the total sample 1871-2017 into two equal parts and estimate regressions for each part. The market states indicate I_{bad} for recessions and I_{good} for expansions. We included predictor variables, time period, β coefficient, the p-value for t-statistics, adjusted R-squared, and differences in adjusted R-squared between two historical subperiods. All p-values are estimated using the Newey-West procedure controlling for heteroskedasticity and autocorrelation. Predicting variables denoted with ***, ** and * are significant on 1%, 5% and 10% levels, respectively.

Table 11: Robustness test of the bull and bear states

Macroeconomic predictor variables	First period						Second period						Imp
	Data	β_{good}	P>$\|t\|$	β_{bad}	P>$\|t\|$	$\overline{R}^2$	Data	β_{good}	P>$\|t\|$	β_{bad}	P>$\|t\|$	$\overline{R}^2$	$\Delta\overline{R}^2$
Dividend-price ratio	1871-1934	0.008	33.8	0.016	6.3*	13.52	1944-2017	0.009	0.1***	0.016	0.0***	18.37	4.85
Earnings-price ratio	1871-1934	0.013	4.3**	0.022	0.2***	14.19	1944-2017	0.006	7.7*	0.014	0.0***	18.13	3.94
Dividend-earnings ratio	1871-1934	-0.040	0.4***	0.030	7.5*	7.32	1944-2017	-0.004	47.7	0.042	0.0***	13.09	5.77
Book-to-market ratio	1921-2017	0.060	0.0***	0.008	51.6	8.21	1969-2017	0.025	0.1***	-0.017	1.5**	6.20	-2.01
Net equity expansions	1926-2017	0.335	2.5**	-0.380	0.0***	4.51	1967-2017	0.020	86.4	-0.119	-11.9***	-0.24	-4.75
T-bill rate	1920-2017	0.384	2.2**	-0.552	0.5***	3.38	1970-2017	0.171	0.5***	-0.204	0.1***	5.62	2.24
Long-term yield	1919-2017	0.106	70.9	-0.163	57.4	0.12	1970-2017	0.021	76.0	-0.033	-3.3***	-0.21	-0.33
Long-term return	1926-2017	0.570	3.2**	-0.397	9.8*	0.99	1967-2017	0.123	9.2*	0.081	44.4	0.25	-0.74
Term spread	1920-2017	0.753	1.0**	-1.148	0.0***	5.61	1970-2017	0.426	0.1***	-0.607	0.0***	5.87	0.26
Default yield spread	1919-2017	1.484	0.0***	-0.932	0.2***	8.83	1970-2017	1.768	0.0***	-0.829	4.5**	9.93	1.10
Default return spread	1926-2017	-0.332	3.9**	0.396	0.9***	4.04	1967-2017	-0.090	7.2*	0.219	0.0***	6.00	1.96
Inflation	1913-2017	0.268	54.5	-0.445	22.8	-0.02	1973-2017	0.851	13.0	-2.460	0.0***	3.29	3.31
Technical variables													
Past monthly return	1871-1934	0.125	8.8*	0.043	61.0	0.69	1944-2017	-0.097	0.5***	0.280	0.2***	2.84	2.15
Conditional variance	1885-2017	2.078	0.0***	-1.367	0.3***	3.17	1951-2017	4.687	0.0***	-1.890	0.0***	7.35	4.18
MOM(12)	1871-1934	-0.006	81.8	0.048	15.5	1.14	1944-2017	0.004	81.4	0.022	62.6	-0.03	-1.17
SMA(10)	1871-1934	-0.002	65.7	0.008	12.7	1.01	1944-2017	-0.003	22.2	0.012	6.6*	1.59	0.58

This table reports the robustness test of two-state predictive regression model by splitting the total sample 1871-2017 into two equal parts and estimate regressions for each part. The market states indicate I_{bad} for bear and I_{good} for bull. We included predictor variables, time period, β coefficient, the p-value for t-statistics, adjusted R-squared, and differences in adjusted R-squared between two historical subperiods. All p-values are estimated using the Newey-West procedure controlling for heteroskedasticity and autocorrelation. Predicting variables denoted with ***, ** and * are significant on 1%, 5% and 10% levels, respectively.

Table 12: Robustness test of the high and low sentiment

Macroeconomic predictor variables	First period						Second period						Imp
	Data	β_{good}	P>$\|t\|$	β_{bad}	P>$\|t\|$	$\overline{R}^2$	Data	β_{good}	P>$\|t\|$	β_{bad}	P>$\|t\|$	$\overline{R}^2$	$\Delta\overline{R}^2$
Dividend-price ratio	1965-1990	0.026	3.1**	0.026	3.0**	0.91	1990-2015	0.013	14.1	0.013	14.7	0.07	-0.84
Earnings-price ratio	1965-1990	0.010	23.6	0.010	22.9	-0.18	1990-2015	0.009	17.7	0.009	19.0	-0.04	0.14
Dividend-earnings ratio	1965-1990	0.023	36.7	0.019	36.8	-0.39	1990-2015	-0.001	85.1	0.000	99.9	-0.65	-0.26
Book-to-market ratio	1965-1990	0.013	33.7	0.012	33.3	-0.33	1990-2015	0.024	44.4	0.022	46.1	-0.46	-0.13
Net equity expansions	1965-1990	-0.449	1.1**	-0.241	19.5	1.75	1990-2015	0.158	26.4	0.460	3.8**	1.11	-0.64
T-bill rate	1965-1990	-0.068	49.7	-0.055	64.8	-0.51	1990-2015	0.071	54.7	0.018	91.8	-0.54	-0.03
Long-term yield	1965-1990	0.061	56.8	0.086	52.3	-0.53	1990-2015	0.032	82.9	0.040	82.2	-0.65	-0.12
Long-term return	1965-1990	0.162	12.0	0.251	5.3*	1.36	1990-2015	0.058	61.8	0.069	55.7	-0.47	-1.83
Term spread	1965-1990	0.414	4.1**	0.252	28.0	0.84	1990-2015	-0.185	39.2	-0.075	71.2	-0.4	-1.24
Default yield spread	1965-1990	1.571	0.5***	2.153	0.2***	2.70	1990-2015	-1.758	5.8*	-1.024	9.3*	0.56	-2.14
Default return spread	1965-1990	0.103	13.3	0.115	14.7	0.21	1990-2015	0.036	65.6	0.043	62.7	-0.57	-0.78
Inflation	1965-1990	-3.082	0.6***	-1.569	4.4**	2.02	1990-2015	0.146	87.5	0.932	36.8	-0.39	-2.41
Technical variables													
Past monthly return	1965-1990	-0.044	59.2	-0.062	44.9	-0.38	1990-2015	-0.011	88.9	0.011	89.8	-0.66	-0.28
Conditional variance	1965-1990	-1.034	9.6*	0.448	83.4	0.33	1990-2015	-1.071	37.0	-1.394	0.7***	1.79	1.46
MOM(12)	1965-1990	-0.019	46.6	0.001	96.1	-0.49	1990-2015	0.031	16.4	0.016	38.6	0.20	0.69
SMA(10)	1965-1990	-0.001	81.8	0.000	98.0	-0.66	1990-2015	0.001	78.1	0.005	12.2	0.15	0.81

This table reports the robustness test of two-state predictive regression model by splitting the total sample 1871-2017 into two equal parts and estimate regressions for each part. The market states indicate I_{bad} for low sentiment and I_{good} for high sentiment. We included predictor variables, time period, β coefficient, the p-value for t-statistics, adjusted R-squared, and differences in adjusted R-squared between two historical subperiods. All p-values are estimated using the Newey-West procedure controlling for heteroskedasticity and autocorrelation. Predicting variables denoted with ***, ** and * are significant on 1%, 5% and 10% levels, respectively.

Table 13: Robustness test of the increasing and decreasing sentiment

Macroeconomic	First period						Second period						Imp
predictor variables	Data	β_{good}	P>$\|t\|$	β_{bad}	P>$\|t\|$	$\overline{R}^2$	Data	β_{good}	P>$\|t\|$	β_{bad}	P>$\|t\|$	$\overline{R}^2$	$\Delta\overline{R}^2$
Dividend-price ratio	1965-1990	0.026	3.1**	0.026	3.0**	0.91	1990-2015	0.014	11.7	0.015	9.5*	0.68	-0.23
Earnings-price ratio	1965-1990	0.010	24.1	0.010	25.7	-0.19	1990-2015	0.007	29.2	0.008	22.1	0.32	0.51
Dividend-earnings ratio	1965-1990	0.016	43.1	0.016	42.4	-0.45	1990-2015	-0.001	81.7	0.001	91.8	-0.62	-0.17
Book-to-market ratio	1965-1990	0.011	38.9	0.013	29.8	-0.31	1990-2015	0.031	29.2	0.011	72.1	0.05	0.36
Net equity expansions	1965-1990	-0.391	2.2**	-0.300	12.1	1.53	1990-2015	0.149	43.3	0.299	4.7**	0.79	-0.74
T-bill rate	1965-1990	-0.074	47.7	-0.058	58.8	-0.50	1990-2015	0.084	50.1	0.025	85.9	-0.51	-0.01
Long-term yield	1965-1990	0.041	72.8	0.058	58.5	-0.55	1990-2015	0.056	70.9	-0.046	77.8	-0.21	0.34
Long-term return	1965-1990	0.008	94.6	0.377	0.1***	3.02	1990-2015	0.016	91.7	0.083	39.9	-0.43	-3.45
Term spread	1965-1990	0.003	21.0	0.378	5.8*	0.74	1990-2015	0.037	86.2	-0.261	20.6	0.44	-0.3
Default yield spread	1965-1990	1.582	1.6**	1.606	0.4***	2.11	1990-2015	-0.038	96.2	-0.845	15.5	0.84	-1.27
Default return spread	1965-1990	0.092	20.7	0.119	9.9*	0.26	1990-2015	-0.033	70.3	0.088	26.6	0.11	-0.15
Inflation	1965-1990	-1.471	9.4*	-2.200	1.3**	1.48	1990-2015	0.114	91.2	0.763	39.7	-0.43	-1.91
Technical variables													
Past monthly return	1965-1990	-0.090	32.2	-0.028	71.3	-0.30	1990-2015	0.063	54.0	-0.031	66.4	-0.48	-0.18
Conditional variance	1965-1990	4.551	14.1	-0.977	11.0	1.28	1990-2015	-1.213	51.5	-1.362	0.7***	1.77	0.49
MOM(12)	1965-1990	-0.040	13.1	0.014	50.1	0.29	1990-2015	-0.002	93.6	0.032	5.8*	0.55	0.26
SMA(10)	1965-1990	-0.007	15.4	0.003	37.8	0.30	1990-2015	0.002	75.7	0.004	16.2	0.01	-0.29

This table reports the robustness test of two-state predictive regression model by splitting the total sample 1871-2017 into two equal parts and estimate regressions for each part. The market states indicate I_{bad} for decreasing sentiment and I_{good} for increasing sentiment. We included predictor variables, time period, β coefficient, the p-value for t-statistics, adjusted R-squared, and differences in adjusted R-squared between two historical subperiods. All p-values are estimated using the Newey-West procedure controlling for heteroskedasticity and autocorrelation. Predicting variables denoted with ***, ** and * are significant on 1%, 5% and 10% levels, respectively.

Reflection note of Filip

To finish a master's degree in Financial Economics, Johnny and I were looking into topics where we could use our theoretical knowledge that we attained throughout our 5-year journey at the University of Agder. We were suggested by our supervisor Valeriy Ivanovich Zakamulin to write a thesis about stock market predictability. The goal was to test the performance of macroeconomic and technical indicators, together with four different definitions of market states. Most of the methods used were applied in previous studies like the one carried out by Welch and Goyal (2008) and Huang et al. (2014).

Our thesis contributed to financial research by examining more recent data, including different macroeconomic and technical variables and evaluating various definitions of good and bad market states. We found interesting results when analyzing those 12 macroeconomic and four technical indicators in the one-state and two-state model regression model. We found that the two-state model has demonstrated better performance for recessions and expansions, and bull and bear markets. However, investor sentiment index has shown poor predictability and seemed unstable.

The writing process of this thesis has been challenging but also exciting and educational. I improved my programming skills using statistical software called Stata and learned how to prepare documents in LaTeX. Also, for us to understand and apply these methodologies, the background materials provided by the University of Agder were essential. Mathematical and financial courses like statistics, research methods, econometrics, and finance theory, were highly relevant.

The predictability of stock returns is very much linked to internationalization. It can be applied in all the countries, indexes of the stock markets and other markets, such as commodity and currency markets. Today, cross-border financial markets are more connected and reliable than ever before. We have observed how other financial markets around the globe were affected by the economic crash in the US in 2008 as an example. There have been higher correlations between different indexes over time, and a lot indicates that relationship only will be stronger in the future. Information is publicly available for all the investors to absorb. And since trading can often be done instantly, portfolio managers can take more data into consideration when investing in stocks and developing portfolios.

Innovation is an essential factor in the financial world. In the last decade, we have observed the rise of big data and algorithmic trading on the stock market. Most of the investment banks and mutual funds utilize computers to some degree when trading. Many would even argue that machines and artificial intelligence will take over the trading world in the near future. And while our study is to some extent a reexamination of other studies, we believe that some of our work is innovative and the use of our approaches and methods presented could be implemented in practice.

Responsibility is also closely linked to the topic discussed. Institutional investors are responsible for other people's money. They are expected to deliver high returns every year but are also expected to operate within the boundaries of the law. In other words, we are expecting a fair trade, no insider information, and robust, long-term investments strategies. Also, we assume that the government and lawmakers act responsible, protect, and control the interest of the people and future generations. However, there have been many instances where financial identities were misusing their trust and advised expensive funds in hope for higher bonuses for themselves. Therefore, I believe that there should be stronger regulation system and higher penalties when financial identity put himself in front of costumer's rights.

Reflection note of Johnny

We chose to write about "Time-varying stock return predictability" in which we could utilize our quantitative knowledge and skills that we have adopted throughout our studies. There is contradicting evidence in the literature, whether there is possible to predict the stock market. We replicated previous studies on this topic to see whether stock return predictability exist in bad economic times. Our thesis examined one-state and two-state linear predictive regression for different macroeconomic variables and technical indicators. In talks with our supervisor we agreed upon how it could be beneficial to compare different definitions of market states to see which one is more sufficient. He argued that bull and bear markets are highly overlooked by researchers, and he also pointed out that it has many advantage over other methods. Our study found mixed performance across the dierent predictors, where a large percentage of these predictors performed better in bull and bear market compared to the other definitions of market states.

When it comes to internationalization, we do see that this topic is closely related to international trends and globalization. In modern times, the development of computers and internet has led to a more interconnected stock markets across countries than ever before. The information of the stock market in different countries are available for any investors, and therefore trades are being executed instantaneously between them. The increasing globalization of world economy creates new and better opportunities for investors to analyze and use different methods of predictability for different derivatives and trading products. Nonetheless, investors should keep in mind that international factors do play a significant role in identifying whether there is a trend of stock return predictability in bad economic states. They have to consider that this trend might be different in some country compared to others, and therefore they have to carefully implement investing strategies that analyze the complex structure of the global economy as a whole.

Our thesis is based on stock return predictability in good and bad economic times where we use different definitions for the market states. Some implications with these markets are due to the fact that investors might overreact to news. This indicate that the market is inefficient and investors seems to be not fully rational, and the existing services do not take this gap into account. In recent times, a new trend is emerging which is based on using artificial intelligence and machine learning to predict stock market returns. These technologies would effect the stock market in a way that it is evolving and moving in a more standardized way. These innovations in the field will likely increase computer power to predict stock return in different economic circumstances.

The importance of responsible investing is one of the most heated discussion in financial industry over the last century. The investment industry appears to be plagued with conflicts of interest, and we know that brokers do not always act and invest within the boundaries of laws and regulations. Some of them want to earn commissions and are therefore under intense pressure to do so. Due to this pressure they are not always investing based on the interest of investors. We do see that some brokers are tempted to sell excessively risky products, even though it is beyond investors preferences. Therefore, institutional investors do have great power because their actions have a great impact on people's economy and welfare. The society has expectation that those with power is obligated to act with high responsibility. However, climate problems are one of the biggest crisis in today's society, and therefore we are expecting that institutional investors should focus on sustainable investments such as renewable energy and climate friendly technologies. Nevertheless, we do see some investment banks or institutional investors that do not focus on sustainable investments nor maximizing customers wealth within the boundaries of law. This hurts the environment among investors. The government should impose stricter penalties for those who break these ethical norms and regulations.