The dynamics of stock market returns and macroeconomic indicators: An ARDL approach with cointegration

SEBASTIAN HAQ & RASMUS LARSSON

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Dynamiken mellan aktiemarknadens avkastning och makroekonomiska indikatorer: En ARDL ansats med kointegration

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Abstract

Macroeconomic indicators are amongst the most important and used tools for investors as they provide an outlook for the economy and thus improve the assessment of investments e.g. for asset allocation. The purpose of this thesis is to investigate the short- and long-run relationship between the US stock market index S&P500 and six selected macroeconomic indicators during different time regimes during 2000-2016. The chosen indicators are Personal spending, Initial jobless claims, M1 Money supply, Building permits, Michigan Consumers Sentiment index and the ISM Manufacturing index as they measure different parts of the economy and are commonly used by investors. We achieve the purpose by using the Autoregressive Distributed Lags model (ARDL) as it has several advantages in relation to comparable time series models. The results show that all indicators except Personal spending are significant in the long-run on the 1-percent level, in at least one time-regime. All indicators have significant results also in the short-run except the Money Supply (M1), depending on which time period that is under investigation. Our conclusion is that our chosen indicators have different characteristics depending on the current dynamics of the stock market, economic state and other related markets. The practical implication for investors is that different indicators are of limited use depending on the current market dynamics and investors must evaluate the underlying premises of the development of the indicator rather than interpreting a specific datapoint.

Keywords: Autoregressive Distributed Lags, ARDL, Macroeconomics, S&P500, Personal Spending, Initial Jobless Claims, M1 Money Supply, Building Permits, Michigan Consumers Sentiment index, ISM Manufacturing index
Sammanfattning


Nyckelord: Autoregressive Distributed Lags, ARDL, Makroekonomi, S&P500, Personal Spending, Initial Jobless Claims, M1 Money Supply, Building Permits, Michigan Consumers Sentiment index, ISM Manufacturing index
Preface

This study was conducted during the spring of 2016 at the Royal Institute of Technology (KTH) for the Department of Industrial Engineering and Management.

We want to express our utmost appreciation and gratitude to our supervisors Tomas Sörensson at the Royal Institute of Technology and Kristoffer Lindensjö at the Department of Mathematics at Stockholm University, for their support and advice. We would also like to thank Kristofer Månsson at Jönköping Universitet for reviewing our work. We would also like to express our gratitude towards our supervisors at SEB Investment Management Kristin Gejrot and Peter Lorin Rasmussen for introducing us to this topic and providing us with valuable support and guidance throughout the thesis.

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Sebastian Haq & Rasmus Larsson
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# Contents

1 Introduction ................................. 1  
1.1 Problematization .......................... 3  
1.2 Purpose and Research Questions ........... 4  
1.3 Outline .................................... 5  

2 Research Design and Methodology .......... 6  
2.1 Method for Conducting Literature Review .... 6  
2.2 Method for Conducting Statistical Analysis ... 7  

3 Literature Review ............................ 9  
3.1 Macroeconomic Indicators and the Stock Market .. 9  
3.1.1 Stock Market and Economic Growth ........ 9  
3.1.2 Investigation of Short-Run and Long-Run Relationship ... 10  
3.1.3 Volatility As a Measurement of Impact .......... 12  
3.1.4 Variable Selection and Time-Setting ........... 12  
3.2 Conclusion and Summary of Literature Review ... 13  

4 Data - Description and Documentation ...... 15  
4.1 Data Collection and Analysis ............... 15  
4.1.1 Time Periods .......................... 16  
4.2 Data Description ........................... 17  

5 Econometric Framework ....................... 20  
5.1 Terminology ................................ 20  
5.2 Linear Regression .......................... 20  
5.3 Spurious Regression ......................... 21  
5.4 Long-run Relationship ....................... 22  
5.5 Augmented Dickey-Fuller Test ............... 23  
5.6 Autoregressive Distributed Lags ............. 24  
5.6.1 Model Specification ..................... 25  
5.6.2 F-Bounds Test and Error Correction Modelling ... 26  
5.7 Application of ARDL ....................... 28  
5.7.1 Lag Selection .......................... 29  
5.7.2 F-bound Test ........................... 29  
5.8 Diagnostic Testing .......................... 30  
5.8.1 Test for Stability ....................... 30  
5.8.2 Test for Serial Correlation ............... 31  
5.8.3 Test for Heteroscedasticity ............... 31  
5.8.4 Regression Specification Error Test .......... 31  
5.8.5 Test for Normality of the Residuals .......... 32  
5.8.6 Economic Significance .................... 32  
5.9 Summary of Econometric Framework .......... 32  

6 Results ..................................... 34  
6.1 Stationary or Non-Stationary Data .......... 34  
6.1.1 ADF-Tests ........................... 34  
6.2 Short-Run and Long-Run Relationships ....... 36  
6.2.1 Results from the ARDL Model .............. 36  
6.2.2 CUSUM and CUSUMSQ Tests ............... 40  
6.2.3 Predicted Versus Actual Values on S&P500 .... 41
7 Analysis and Discussion of Findings

7.1 Macroeconomic Interpretation

7.1.1 Initial Jobless Claims

7.1.2 Building Permits

7.1.3 M1 Money Supply

7.1.4 Michigan Consumer Sentiment Index

7.1.5 Personal Spending

7.1.6 ISM Manufacturing

7.1.7 Process for Evaluating the State of the Economy

7.2 Discussion on Model Implications

7.2.1 Measurement of Importance

7.2.2 Quality of Scientific Work

8 Conclusion and Implications

8.1 Suggestion for Further Research

References

A Appendix - Additional Tables

A.1 Tables for Period 1

A.2 Tables for Period 1a

A.3 Tables for Period 1b

B Appendix - Additional Figures

B.1 Data

B.2 First Differenced Data

B.3 Predictions

B.4 ACF Plots
List of Figures

1. The US stock index S&P500 ........................................ 2
2. Summary of Mathematical Methodology Applied in this Study .... 8
3. The US stock index S&P500 divided into two time series .......... 16
4. Example of a Stationary time series ................................ 21
5. Example of a Non-Stationary time series ............................ 21
6. Example of a Cointegrated pair ...................................... 23
7. Example of CUSUM test .............................................. 30
8. CUSUM for period 1 .................................................. 40
9. CUSUMSQ for period 1 ................................................. 40
10. CUSUM for period 1a .................................................. 40
11. CUSUMSQ for period 1a ................................................. 40
12. CUSUM for period 1b .................................................. 40
13. CUSUMSQ for period 1b ................................................. 40
14. Prediction vs Actual S&P500 Values for Period 1 ................. 41
15. Scatter plot of Prediction vs Actual S&P500 Values for Period 1 41
16. Prediction vs Actual S&P500 Values for Period 1a ................. 42
17. Scatter plot of Prediction vs Actual S&P500 Values for Period 1a 42
18. Prediction vs Actual S&P500 Values for Period 1b ................. 42
19. Scatter plot of Prediction vs Actual S&P500 Values for Period 1b 42
20. Out-of-Sample Prediction vs Actual S&P500 Values ............... 43
22. Inverted IJC compared to S&P500 ................................... 46
23. Building Permits and S&P500 ....................................... 48
24. Liquidity Preference Model of the Interest Rate .................. 50
25. Money Supply (USD Billion) between 1981-2016 .................. 51
26. Money supply (USD Billion) and QE action by FED ............... 51
27. S&P500 and Michigan Consumer .................................... 52
28. Personal Savings Rate ............................................... 54
29. ISM Manufacturing ................................................... 55
30. Refined Mathematical Methodology of State of Economy used in this Study 57
31. The development of Michigan Consumer and IJC ................. 72
32. The development of ISM manufacturing and Building Permits .... 72
33. The development of M1 and Personal Spending ................... 72
34. First Difference of Michigan Consumer and IJC .................. 73
35. First Difference of ISM manufacturing and Building Permits ...... 73
36. First Difference of M1 and Personal Spending .................... 73
37. Prediction vs Actual S&P500 Values for Period 1 ................. 74
38. Prediction vs Actual S&P500 Values for Period 1a ................. 74
39. Prediction vs Actual S&P500 Values for Period 1b ................. 75
40. Out-of-Sample Prediction vs Actual S&P500 Values ............... 75
41. ACF Plot Residuals Period 1 ........................................ 76
42. ACF Plot Residuals Period 1a ....................................... 76
43. ACF Plot Residuals Period 1b ....................................... 76
List of Tables

1 Literature Review - Keywords ........................................... 7
2 Macroeconomic Indicators ............................................. 17
3 Description of Indicators ............................................. 19
4 ADF test for period 1 .................................................... 35
5 ADF test for period 1a .................................................. 35
6 ADF test for period 1b .................................................. 35
7 ADF Critical Values ................................................... 35
8 Final ARDL results ..................................................... 38
9 Diagnostic tests and F-bound test-statistics for the main ARDL models 39
10 Predictors over- or underestimate the actual values .................. 42
11 Summary of the results .............................................. 62
12 ARDL for the entire period .......................................... 68
13 ARDL for the period 1a ............................................... 69
14 ADF test adjusted for financial crisis (Period 1a) .................... 69
15 ARDL for the period 1b ............................................... 70
16 IJC and MC relationship Comparison .............................. 70
17 Critical values for IJC and M1 comparison ........................ 71
Nomenclature

$H_0$  Null hypothesis in a regression

$H_1$  Alternative hypothesis in a regression

$I(d)$  Stationarity of order $d$

$n$  Sample size

$p_j$  Lag selection

$R^2$  Goodness of Fit for a regression

$t$  Time unit measured in months

$y_t$  Time series value at time $t$

$Z$  Integer numbers

BP  Abbreviation for Building Permits indicator

IJC  Abbreviation for Initial Jobless Claims indicator

ISM  Abbreviation for ISM manufacturing indicator

M1  Abbreviation for M1 money supply indicator

MC  Abbreviation for Michigan Consumer indicator

Period 1  The Period around 2000-2016

Period 1a  The Period around 2000-2009

Period 1b  The Period around 2009-2016

PS  Abbreviation for Personal Spending indicator

SP500  Abbreviation for S&P500 stock market index
1 Introduction

The decision on how to construct a portfolio of assets is one of the most important financial decisions of both institutions and individuals. In the construction of a diversified portfolio, i.e. a portfolio that is not greatly affected by market volatility, the investor has to carefully develop a decision process for determining appropriate investment criteria for each asset in the portfolio to receive an acceptable level of risk in relation to the expected return. The portfolio allocation process is extremely critical and has to be carefully prepared as a poor choice of assets may increase the portfolio risk and induce large capital losses.

Having a well-diversified and carefully prepared portfolio is no guarantee against losses, as there are many factors that interact in the financial market including political events, the worldwide economic situation and investor expectations (Huang et al. 2005). The stock market is considered to be a concurrent part of the economic development as it inter alia allows for redistribution of wealth e.g. it can be used to raise capital for businesses by an initial public offering (IPO) allowing the businesses to obtain the necessary capital injection and investors to invest their savings in an reliable manner. Furthermore the macroeconomic development and investor expectations may induce stock market movements as fluctuations in the macroeconomic environment and expectations affect future consumption (Chen 2009) and may also alternate the number and different types of available real investment opportunities (Flannery & Protopapadakis 2002). Consequently, variations in macroeconomic conditions simultaneously affect numerous firms cash flows (Flannery & Protopapadakis 2002). As companies create value for their owners by investing cash now to generate greater cash flows in the future (Koller et al. 2015) the economic development and investor expectations will affect the corporate valuations and thus the stock market development. Consequently the stock market can illustrate expectations of the future development of the economy.

The emerging Dotcom Bubble in late 1990s to the early 2000s is an exceptional example of how the stock market can develop due to investor expectations in terms of optimism and confidence, in this case related to Internet based companies. The combination of tremendous confidence and available capital funding made the technology based US stock index NASDAQ rise from 1500 to 5000 during 1997-2000 before it crashed in the following years. As a consequence of the bubble, the industrial production decreased rapidly but reached a turning point in mid 2003 whereby the stock market began to increase. The increased industrial production in combination with a strong housing sector where the number of building permits almost reached an all-time high fueled the stock market even further. A more recent event affecting the entire market is the introduction of Quantitative Easing (QE) by for example the US Federal Reserve (FED), Bank of England (BoE) and the European Central Bank (ECB). QE is an unconventional monetary policy for which a central bank purchase domestic government securities from the market in order to reduce deflationary forces (Joyce et al. 2012). QE therefore increase the money supply for financial institutions which promote increased lending and liquidity leading to lower interest rates. As the acquirement of capital becomes cheaper the economic output in terms of e.g. investments and consumer spending
1. Introduction

Haq, Larsson will increase and so will the corporate valuations. Furthermore, the reduced interest rates lower the returns for risk-free interest bearing assets making investments in other assets more attractive. Thus investors may for example shift their portfolios towards a higher weight of equity, which in turn increase the stock prices. After the financial crisis the stock market has been in a positive trend but with both downturns (Debt ceiling debate) and upturns (Increased overall consumer confidence). The conclusion from these illustrative examples (visualized in Figure 1) is that the dynamics and interrelations of several factors induce uncertainty regarding investments in the market. Market participants e.g. institutional investors has therefore for a long time had a great interest in creating reliable stock market predictions (Chen 2009).

![Figure 1: The US stock index S&P500. The grey areas are US recessions determined by NBER (2016). Source: Bloomberg, Macrobond, NBER, US Department of Labor, US FED, Authors computations](image)

To mitigate the uncertainty in the market and consequently establish a solid basis for portfolio allocation it is of importance not only to investigate and analyze the individual stocks themselves but also include external economic and political factors and how they affect the market.

The influence on the financial markets of economic and political factors including market expectations can be captured in macroeconomic indicators such as the unemployment rate (Boyd et al. 2005), business confidence surveys and manufacturing production indexes (Nasseh & Strauss 2000). A macroeconomic indicator is often a statistical measurement of a part of the economy and/or the business cycle and in general they are inter alia used by investors to evaluate the overall health of the economy and to detect investment opportunities. As the stock market is a concurrent part of the economy and stock prices are often determined on a cash flow basis a common view is that fundamental macroeconomic indicators can
influence stock market prices and be included in the portfolio investment decision (Pilinkus 2010, Chen 2009).

In conclusion it can be argued that a part of the portfolio allocation process should be to carefully analyze and evaluate the market and consequently related macroeconomic indicators. This is particularly important as investors can gain a greater understanding of the stock market and thus develop methods and models for how the stock market will evolve due to changes in the economy. The considered predictability from studies of the relationship between economic activity and the stock market allows investors to develop market-timed strategies (Chen 2009). The investor is also enabled to adjust their market expectations so that the portfolio corresponds to the investors outlook, risk-tolerance and required rate of return.

1.1 Problematization

In a competitive market such as the financial market it is important for e.g. portfolio managers to continuously produce high-performing portfolios to attract external investors and consequently increase portfolio assets under management. Therefore it is critical that managers improve their risk and return assessment methods by making an effort to develop their understanding of the market. Which if done successfully may lead to increased portfolio returns and consequently increased inflows of capital to the fund/business. The problematization of improving the risk and return profile also exists for other professionals including financial institutions, organizations or individuals that are interested in capital management.

As previously described, due to political and economic factors uncertainty is created on the financial markets. Practitioners have therefore developed and now use macroeconomic indicators to assess the current market sentiment to manage the portfolio allocation. In this setting, we consider three practical aspects.

Firstly, the correctness of the indicators i.e. the indicators measure what they are supposed to measure is extremely important as they lay the foundation for predicting market movements and accordingly affect investment choices. An indicator that provide an incorrect overview of the part of the economy it is supposed to measure may therefore induce losses and decrease portfolio returns.

Secondly, in order to be able to prioritize between indicators it is important to analyze if the indicators actually have a short-run and/or long-run relationship with the market (See Section 5.1 and Section 5.6.1 for a definition of short/long-run relationship). In detail, to expand the concept and application of macroeconomic indicators the appropriateness of each indicator and their causality/correlation with the market should be under investigation in order to be able to prioritize between indicators when they e.g. propose different directions of the market.

Finally, the indicators importance may change depending on certain time periods as the financial market is continuously changing with new arising market conditions. For example Boyd et al. (2005) and Knif et al. (2008) demonstrated the
importance of incorporating the time perspective when evaluating macroeconomic indicators in their study of stock market reactions of macroeconomic news. Boyd et al. (2005) study suggest that on average, stock prices fall after bad labor market news during economic contractions and rise during economic expansions. A similar result is observed by Knif et al. (2008) who suggest that inflation shocks may have different effects on the stock market depending on the economic state. Thus it is critical to evaluate the current market conditions when analyzing macroeconomic indicators.

On the basis of inter alia, the competitiveness in the financial industry investors are required to constantly try to improve their understanding of the market for obtaining increased returns through a better risk profile. We will therefore investigate if a certain set of macroeconomic indicators may provide information of the future stock market development. Additionally, to gain a further understanding of macroeconomic indicators we examine whether there exists underlying short- and/or long-run relationships between the indicators and the stock market and if the relationships are dependent on certain time periods. Overall this study may provide both a systematic approach of assessing market sentiment and insights of how e.g. investors may improve their asset allocation process. For example by utilizing macroeconomic indicators an investor can adjust his market expectations such that his investments e.g. a portfolio of assets corresponds to his outlook, risk-tolerance and required rate of return.

1.2 Purpose and Research Questions

The purpose of this thesis is to investigate the relationship between certain macroeconomic indicators and the US stock market development in the short- and the long-run. The stock market index under consideration is S&P500 as it is one of the most common stock indices and is often used as a proxy for the US stock market. Furthermore, as S&P500 covers the 500 largest publicly traded companies in the United States it can be expected that changes in the business cycle and different macroeconomic indicators affect the index. The following indicators will be under investigation in this thesis as they measure different parts of the economy and are commonly used by investors.

1. ISM manufacturing index
2. Michigan Consumer Sentiment index
3. Initial Jobless Claims
4. M1 money supply
5. Personal Spending
6. Building Permits

The time periods of choice are 2000-2016, 2000-2009 and 2009-2016. We achieve the purpose by investigating the short-run and long-run impact of the given indicators using the Autoregressive Distributed Lags model (ARDL) as it has several advantages in relation to other methods. The thesis focuses on the following Research Questions (RQ) in order to fulfil the purpose:
RQ 1.0 How can the set of macroeconomic indicators be used to describe the stock market development?

This research question can be divided into the following sub-questions:

RQ 1.1 What are the short and long-run relationships between our chosen set of macroeconomic indicators and the US stock market?

RQ 1.2 Do the set of macroeconomic indicators have different relationships with the stock market during different time periods?

RQ 1.3 Which and when are the macroeconomic indicators most important for describing the stock market development?

1.3 Outline

The thesis follows the structure given below.

Section 2 - Research Design and Methodology This Section describes the research design and the general methodology for the thesis work.

Section 3 - Literature Review The literature review is presented covering relevant research within the field and common econometric models. The expected contribution in relation to previous research is also mentioned.

Section 4 - Data - Description and Documentation The Data collection and the chosen macroeconomic indicators are described.

Section 5 - Econometric Framework The econometric model, ARDL is described and the applied model is derived. Complimentary tests i.e. diagnostic tests for the ARDL model are then explained.

Section 6 - Results The results from the ARDL model and the complimentary tests are presented.

Section 7 - Analysis and Discussion of Findings The findings from Section 6 are described from a macroeconomic perspective. A discussion about the measurement of importance and the quality of scientific work is also given at the end of the section.

Section 8 - Conclusion and Implications Concluding remarks and a summary of the research findings are given as well as suggestions for further research.
2 Research Design and Methodology

In this section the research design and methodology are described and explained. The econometric model (see Section 5) and the data (see Section 4) to be included in the analysis will not be explained in this section. Rather the general research design is motivated including a literature review process with, amongst other things, relevant keywords.

This thesis investigate the relationship between six macroeconomic indicators and the US stock market. Most of the research covering the relationship between macroeconomic indicators and the stock market are of a quantitative nature with a close connection to statistical analysis. This is intuitive as econometric models provide a context and often include trustworthy tools for analyzing relationships between variables.

On the basis of the problem formulation we intend to follow a similar framework as previous research meaning that the thesis have a quantitative approach using a statistical method. The statistical method of choice is Autoregressive Distributed Lags (ARDL) which is a fairly new but increasingly popular model for the determination of short-run and long-run relationships between a given set of variables. ARDL and its characteristics and advantages in relation to other econometric models is described in Section 5.6. As an econometric method is used, this thesis have the following characteristics:

1. Usage of fairly large/medium samples in an econometric setting.
2. Hypothesis testing to determine significance of the short- and the long-run relationships.
3. Produce objective and precise quantitative results.

Thus in accordance with Collis & Hussey (2014) definition of positivist research, we consider a positivist approach to answer the considered research questions. The positivist approach entails that the study will be conducted in the four steps listed below. Note that the steps are not static but rather provide a general guideline for the thesis work.

1. Literature review to gather relevant knowledge
2. Data collection and analysis
3. Modeling and computations using the ARDL model
   - Find long-run relationship
   - Find short-run relationship
4. Analyze the results and provide conclusions

2.1 Method for Conducting Literature Review

The literature review aims to increase the understanding of macroeconomic indicators and their connection to the stock market. To validate our research it is important to relate the results with previous research as well as with macroeconomic theory and hence it is important to gain a general understanding of the
topic and related methods. The research field regarding macroeconomic indicators and their connection to the stock market are therefore to be covered not only to gain a further understanding of the concepts in general but also to determine relevant computational methodologies for our research.

The main content of our research will be acquired through KTHB Primo (KTH library search engine) from essential external databases such as JSTOR, Stern and ScienceDirect. Our aim is to find articles published in peer-reviewed academic journals such as the Journal of Banking and Finance, Journal of Business & Economic Statistics and the Journal of Finance.

Several keywords covering macroeconomics, statistical methods and more general topics will be used to search for relevant literature. The keywords can be seen in Table 1. These keywords will be combined with the use of Boolean operators to acquire more detailed research papers and to gain more specialised knowledge about certain topics.

<table>
<thead>
<tr>
<th>Topic</th>
<th>Keywords</th>
</tr>
</thead>
<tbody>
<tr>
<td>Macroeconomics</td>
<td>Macroeconomic indicators, Macroeconomic fundamentals, Leading/Lagging indicator, Business Cycles, Economic Cycles, Building permits, M1 money supply, ISM manufacturing, Personal spending, Michigan Consumer Sentiment Index, Initial jobless claims</td>
</tr>
<tr>
<td>Statistical methods</td>
<td>Vector Autoregressive Model, ARDL, Long- and short-term relationship, Cointegration, Times series analysis, Johansen’s test</td>
</tr>
<tr>
<td>General topics</td>
<td>Stock Market, S&amp;P500, Price trends</td>
</tr>
</tbody>
</table>

The literature review will be conducted throughout the entire thesis work and become more detailed further into the process. The literature review will be a necessary part of the analysis of the results as it provides relevant knowledge in order to interpret the computational results in a proper manner and to refine the model approach.

2.2 Method for Conducting Statistical Analysis

Statistical methods are going to be used to test 12 general hypotheses for each of the time periods 2000-2016, 2000-2009 and 2009-2016, namely whether there are long-run and short-run relationship between our dependent variable S&P500 and the six different independent variables Building permits, M1 Money Supply, Michigan consumer, Initial jobless claims, ISM Manufacturing and Personal spending. The mathematical tools for hypothesis testing are further explained in Section 5. An example of the hypothesis for the variable Building permits follows below:

- **Hypothesis 1**: There is a long-run relationship between S&P500 and Building permits.
2. Research Design and Methodology

- **Hypothesis 2**: There is a short-run relationship between S&P500 and Building permits.

Due to the complexity of the econometric model several other important diagnostic and hypothesis tests will be discussed further after the introduction of the ARDL model in Section 5. However, the mathematical methodology can be summarized in essentially the following three steps illustrated in Figure 2:

1. Firstly, for a given time period we select and obtain data of the relevant macroeconomic indicators and the stock market index (See Section 4). The data will then be utilized in the next step.

2. Secondly, we will utilize the ARDL model in order to determine the existence of different relationships between the indicators and the stock market (See Section 6).

3. Finally, in order to answer the research questions the results from the previous step will be analyzed on the basis of e.g. macroeconomic theory. Given the analysis it will be possible to provide conclusions of how the indicators can be utilized (See Section 7).

![Figure 2: Summary of Mathematical Methodology Applied in this Study](image-url)
3 Literature Review

The main purpose of the literature review is to provide knowledge and a context regarding previous research of macroeconomic indicators and their relationship to the stock market. The literature review will also be conducted in order to explain and define the scope of the research questions that were defined in Section 1.2 and to clarify relevant topics that could form the basis for further research of our thesis. On the basis of the literature review we will design and determine relevant theoretical frameworks for our research area.

In this section we describe the main literature, results and methods used within the field of short-run and long-run relationships between the stock market and selected macroeconomic indicators.

3.1 Macroeconomic Indicators and the Stock Market

Macroeconomic activity affect future consumption (Chen 2009) and may also induce a variability of the quantity and different kinds of available real investment opportunities (Flannery & Protopapadakis 2002). Macroeconomic indicators are statistical measurements that try to inter alia capture these aspects. In general macroeconomic indicators measure the condition of the economy from a certain aspect and are often concerned with the behavior and performance of an economy as a whole instead of a specific market. As they measure economic activity they are connected to the economic growth as proposed by Chen (1991) who studied the relationship between macroeconomic indicators such as the lagged production growth rate, the default premium, the term premium, the short-term interest rate and the market dividend-price ratio and the US growth rate. Due to their connection to the economy, financial analysts have for a long time been using macroeconomic indicators to predict and make an assessment of the economic development.

Furthermore, as the stock market is assumed to be a concurrent part of the economy many economists have investigated the dynamics between macroeconomic factors and stock returns. The topic has been evaluated inter alia on the basis of different indicators and econometric models ranging from volatility based models to simple ordinary least squares estimations. Research within this topic will be described in the following section.

3.1.1 Stock Market and Economic Growth

One of the most prominent research papers within the field is the early work by Fama (1981) and his study of the correlation between the economy and real stock returns between 1953-1987 using regression methods. He found evidence for a positive correlation between real stock returns and economic measurements such as capital expenditures and average real rate of return on capital. Building on his previous research, Fama (1990) found that annual stock returns are highly correlated with future expected production growth rates. Schwert (1990) replicated the research by Fama (1990) with data between 1889-1988 and found similar results indicating a robust relationship between production and the stock market. Although the research is timeworn, the relationship between the economy and the
stock market remains relevant which was supported by Sirucek et al. (2012) who utilize regression analysis to conclude that S&P500 and Dow Jones are affected by economic activity. Hence it seems that the connection between the economic growth and the stock market is evident. However in contrast to previous research Chen (2009) found conflicting results by utilizing multiple regression analysis to conclude that the expected excess market return is negatively related to the recent GNP growth albeit it is positively related to the future expected GNP growth. This suggests that indicators can affect the stock market not only by providing a current overview of the economy but also by providing insights of the future economic development. The relationship between the stock market and the future performance of the economy can be explained by the fundamental usage of discounted cash flow models for corporate valuations and by the interpretation of systematic risk.

The first concept of discounted cash flows is intuitive as variations in macroeconomic conditions simultaneously affect the cash flows of firms (Flannery & Protopapadakis 2002) and since firms create value by increasing the cash flow outtake the corporate valuations will alter thereafter. The second concept relating to the systematic risk can be linked through the Arbitrage Pricing Theory (APT) (Ross 1976) where multiple risk factors including the future economic performance can explain asset returns i.e. underlying risk factors influence future asset returns.

3.1.2 Investigation of Short-Run and Long-Run Relationship

With the introduction of more advanced econometric models in recent years the topic seem to have attracted even more research. The more recent research regarding the stock markets relation to macroeconomic indicators often seem to be to investigate and evaluate the long-run and short-run relationships between the chosen macroeconomic indicators and the domestic stock market. Indicators that are commonly of interest are GDP, interest rates, Consumer Price Indices (CPI), Industrial Production (IP), risk premium and exchange rates given a certain time period. To examine the validity of a long-run relationship or equilibrium there exist many different methods which are normally related to Johansen’s Cointegration Technique (Johansen 1991), Vector Autoregression (VAR), Vector Error Correction (VECM), Granger/Enger causality (Engle & Granger 1987) and the Autoregressive-Distributed Lags model (ARDL) (Pesaran & Shin 1998, Pesaran et al. 2001).

Most of the studies using these econometric models propose that macroeconomic factors do affect stock market prices regardless whether developed or underdeveloped countries are being considered. Nasseh & Strauss (2000) proposed the existence of a long-run relationship between stock prices and the macroeconomic activity in six major countries in Europe i.e. Germany, France, Italy, the Netherlands, Switzerland and the UK using Johansen’s Cointegration Technique. They conclude that that the stock market is driven by economic fundamentals and interrelated factors such as production, business expectations, interest rates and the CPI. Similarly Chaudhuri & Smiles (2004) found equivalent results for the Australian market whereby the presence of a long-run relationship between real
activity measured in oil prices, GDP, private consumption and the money supply and the stock market was evident. For considerably smaller and more undeveloped economies such as Pakistan and Jordan the results remain fairly similar. Bekhet & Matar (2013) and Hasan & Nasir (2008) utilized an ARDL approach to assess the relationship between macroeconomic indicators and the Jordanian and Pakistan stock market respectively. Using similar indicators as the previous mentioned studies Bekhet & Matar (2013) and Hasan & Nasir (2008) concluded that there is a significant relationship between the indicators and the stock market.

Despite the existence of a large literature base within this research field and that the choice of econometric methods and explanatory variables are fairly similar, the proposed relationships are often inconclusive indicating that the existence of relationships are evident but which macroeconomic variables that are significant are different in different studies. A possible reason for the disparity between the research papers is that the literature within this field is widely disseminated with research for an extensive variety of countries ranging from major economics such as United States and Japan (Humpe & Macmillan 2009) and Australia (Chaudhuri & Smiles 2004) to smaller economies such as the Baltic states (Pilinkus 2010), Singapore (Maysami & Koh 2000) and Ghana (Kyereboah-Coleman & Agyire-Tettey 2008). As different economies are built up and functions in different ways, it is credible that different economies are idiosyncratic to some extent implying that the results from the studies of different countries may become dissimilar.

The disparity between research within the field can be illustrated by the research by Humpe & Macmillan (2009), Maysami et al. (2004) and Kyereboah-Coleman & Agyire-Tettey (2008). They explored the impact of macroeconomic indicators such as industrial production, CPI, money supply and interest rates on the US/Japanese, Singapore and Ghana stock market respectively using the Johansen’s Cointegration Technique and Error Correction Modelling. The results indicate that the US, Japanese and the Singapore stock market in similarity with the Australian and European markets have a long-term relationship with the macroeconomic variables and the domestic industrial production index have a positive and significant impact on the markets. In the US market, money supply has an insignificant impact on the market while for the Japanese market the money supply has a significant and negative impact. In contrast the Singaporean market has a positive and significant relationship with the money supply. Furthermore in Singapore inflation seems to have a positive impact on the market while the opposite occur in Ghana.

Overall the results from these studies suggest there exists a relationship between the economy and the stock markets, although the significance and impact of certain variables tends to be different. The overall conclusion is that due to the diversity between economies and the similarity in the choice of variables, our selection of relevant macroeconomic indicators should not be based on previous research of other countries. Rather the selection should be based on the relevance for the US market and to provide uniqueness from the perspective of other studies.
3. Literature Review

3.1.3 Volatility As a Measurement of Impact

To assess the importance of certain indicators it can be appropriate to analyze the price variations of the stock market following the announcements of the indicators as high priority announcements may induce higher volatility on the market than non-prioritised announcements. The volatility measured by the standard deviation or the variance of the stock market returns is often used as a measurement for risk of a financial asset (Brooks 2014) and thus many researchers have utilized the concept of volatility to assess the impact of macroeconomic indicators. Autoregressive Conditionally Heteroscedastic (ARCH) and Generalised Autoregressive Conditionally Heteroscedastic (GARCH) models are often used to assess the volatility.

Flannery & Protopapadakis (2002) utilized a GARCH model to investigate the impact of 17 macro series announcements during 1980-1996 on the US stock market. Flannery & Protopapadakis (2002) found that six of the variables are strong risk factor candidates where two affect the stock price level return (CPI/Purchasing Price Index(PPI)) and three affect the returns conditional volatility (Balance of Trade, employment report, housing starts) and the final indicator affect both the level and the conditional volatility (Monetary supply M1). These six variables appear to be important parts of the economy as similar studies found closely connected results (Graham et al. 2003). Furthermore Graham et al. (2003) states that the employment report and manufacturing in terms of the National Association of Purchasing Management index (NAPM) have the greatest impact on stock valuation. The impact of manufacturing therefore seems to be evident despite the choice of method as the studies described in Section 3.1.2 provide similar results.

3.1.4 Variable Selection and Time-Setting

As most studies covering the short-run and long-run relationships between a given stock market and the economy are quite similar in the mathematical modeling but not result-wise, two practical aspects can be discussed:

- Choice of standard variables
- Fixed time setting

Firstly, e.g. for a portfolio manager it is of interest to investigate the relationship between the stock market and macroeconomic variables not only for commonly used variables such as GDP and inflation as the practical utilization of the results may be limited. For instance, GDP measures the output of the entire economy and can be broken into several different components e.g. factory orders and consumer spending which are presented only quarterly. Therefore, there are several reasons from the perspective of a portfolio manager to evaluate indicators which are published with a higher frequency and more detailed macroeconomic indicators to achieve a greater understanding of the economic development and subsequently future changes in the stock market. Even though some previous research utilize less general indicators such as oil prices (Chaudhuri & Smiles 2004), housing starts (Flannery & Protopapadakis 2002) and NAPM(Graham et al. 2003) most research
tend to incorporate only standard macroeconomic variables and it seems that the literature regarding more detailed indicators is scarce. In this thesis we intend to expand the existing research by investigating the relationship between the US stock market and more specific macroeconomic indicators presented in Section 4. The results could be of interest for portfolio managers, private investors, pension funds and other investors using macroeconomic indicators.

Secondly, in addition to the practical aspects of primarily exploring basic variables such as GDP and interest rates, the literature regarding the impact of macroeconomic variables on the basis of certain time periods that may change the interrelation between the variables and the stock market seems to be scarce i.e. most research has a fixed time-setting. The time-setting of choice regarding the investigation of the economy’s relationship to the stock market can be of great importance. Perez-Quiros & Timmermann (2000) proposed that the conditional distribution of stock returns is significantly different in recessions and expansions. They argue that changes in interest rates, default premiums and monetary growth have a bigger impact on expected returns during recessions. Similarly Boyd et al. (2005) investigated the impact of labor market news e.g. unemployment rates on stock prices and concluded that on average rising unemployment have a positive impact on stocks during expansions and a negative impact during contractions. Likewise the study by Knif et al. (2008) support the existence of time periods as they observe that inflation shocks may have different effects on the stock market depending on the economic state. This thesis intends to investigate the time aspect between the economy and the stock market and thereby provide greater understanding of the relationship.

3.2 Conclusion and Summary of Literature Review

After a comprehensive literature review we can conclude that the literature regarding macroeconomic indicators and their impact on the stock market is extensive. The previous research has inter alia tried to explain the stock market using several different indicators ranging from the Gross Domestic Product (GDP), CPI, Exchange rates to inflation using a range of statistical methods.

In this thesis we will investigate if and how certain macroeconomic indicators may have a relationship with the US stock market development in the short- and the long-run. To answer the considered research questions this thesis covers several theories and empirical studies within the field of finance and computational statistics. The aim is to combine the financial and the mathematical aspects using a quantitative approach to determine the importance of the given indicators and consequently if individuals and organizations may utilize the indicators to better understand the stock market given a certain time period. The study cover six macroeconomic indicators and how they may describe the US stock market development. The stock index under consideration is S&P500. Due to the complexity of the stock market no single indicator will be able to capture all the aspects of the stock market development. Rather we expect to contribute to the existing literature by expanding the knowledge about the given indicators to gain a greater understanding of interactions between economic development and stock market
movements. The expected contribution of this thesis is therefore that we expand the current research by investigating stock market indicators on the basis of various practical perspectives:

- **Time periods** - Do the set of macroeconomic indicators provided in Section 4 have a relationship with the stock market during the following time periods: 2000-2016, 2009-2016 and 2009-2016. The time periods are motivated in Section 4.

- **Confirmation of consensus** - Which of the given macroeconomic indicators has the most evident relationship with the US stock market movements and do the results confirm consensus regarding the indicators?

Overall this study may provide insights on how e.g. investments professionals and financial organisations could react to changes in the indicators by providing a systematic approach of assessing the market development. Investors can thereby e.g. adjust their market expectations to produce a portfolio that corresponds to their outlook, risk-tolerance and required rate of return. Furthermore by classifying different economic periods and analyzing the stock market indicators on the basis of these periods one can gain a further understanding of the financial market, which for practitioners and academics alike is highly relevant.
4 Data - Description and Documentation

In this thesis we investigate the relationship between a set of indicators and the US stock market. The S&P500 will serve as a proxy for the US stock market as it is regarded by financial professionals as one of the best measures of large-cap equities in the US. Approximately 9 trillion USD is benchmarked against the S&P500 index whereas the constituents account for 2.2 trillion USD. In the following section we motivate and explain the choice of the macroeconomic indicators. The data sample will also be divided into two sub-sets based on underlying characteristics for each sample. This is in order to investigate if the indicators relationship change depending on the different market conditions.

4.1 Data Collection and Analysis

Secondary data in terms of historical prices for S&P500 and the macroeconomic indicators were collected in this thesis. The data considers the US economy since it is the market under consideration. The indicator data as well as the data for S&P500 was provided by the financial software Bloomberg and Macrobond.

The time period of choice is between the end of 2000 to the beginning of 2016 as the research aims to be up to date. The period of choice covers some events that have imposed challenges for the stock market including the fall of the investment bank Lehman Brothers in 2008. The study is however conducted on two more time periods by dividing the sample into two sub-samples. By covering three different time periods we expect to assess if different market conditions and/or events affect the market and accordingly be able to determine if they actually have an effect on the market. A further analysis is given in Section 4.1.1.

The frequency of choice is monthly as most of the data is presented on a monthly basis and therefore the number of data points amounts to 190. The indicators published on a higher frequency e.g. weekly/daily was adjusted to a monthly frequency by taking the latest publication closest to the monthly release of all other indicators. This is in order to best capture the impact of the publication. The problem of using monthly data is that the indicators may have a short-run relationship with the stock market e.g. a day or a week which could be missed in the computation using monthly data. However it can be argued that a monthly frequency will be able to capture business cycles as the entire economy regularly does not change dramatically on a daily/weekly basis disregarding market bubble events. This in combination with that a majority of the data is published on a monthly basis lead us to believe that a monthly frequency is sufficient.

Other secondary data such as detailed facts was collected from the US Bureau of Labor Statistics, US National Association of Home Builders (NAHB), FED and Organisation for Economic Co-operation and Development (OECD) which are prominent and established organizations.
4.1.1 Time Periods

We conduct our study on three different time intervals to assess if the indicators have different relationships with the stock market given different market conditions. Following Brooks (2014) methods for determining appropriate sub-parts, the analysis in addition to the entire period 2000-2016 (period 1), was conducted on the time periods between 2000-2009 (period 1a) and 2009-2016 (period 1b). The first period consist of 110 data points and the second period consists of 80 data points (see Figure 3).

Both the period between 2000-2009 and 2009-2016 are interesting and quite diverse in terms of the market conditions. Between 2000-2009, the economy was growing at a fast-pace with a strong housing sector up to year 2006 (Krugman & Wells 2013) and FED interest rates around 1.5 % - 6 % (OECD 2016A). The period is extended over 2008 to cover the entire financial crisis to allow the market to re-adjust for new market conditions. In contrast, the period between 2009-2016 consists of low GDP growth, unconventional monetary policy in terms of quantitative easing and consequently low FED interest rates around 0.25 % (OECD 2016A,B).

By investigating the long-run and short-run relationships during all time periods we expect to be able to answer questions regarding if different market conditions may affect the interpretation of the indicators e.g. did the housing boom between 1997-2004 render housing indicators to be useless for determining the stock market and has quantitative easing made other indicators less important?

![Figure 3: The US stock index S&P500 divided into two time series. Source: Bloomberg, Macrobond](image)

The entire period (Period 1) analysis will provide insights as by increasing the sample size in relation to the other time periods, disruptions and non-regularities can be diluted by the sample size and may provide a more general analysis of the indicators.
4.2 Data Description

The selected macroeconomic indicators to be investigated are ISM manufacturing, Michigan consumer sentiment index, Building permits, Initial jobless claim, Personal spending and M1 Money supply and their abbreviation can be seen in Table 2. The abbreviations are used when deriving the econometric framework in Section 5. For the interested reader the time series plots can be seen in Appendix B.1.

Table 2: Macroeconomic Indicators. Source: See Publishers below

<table>
<thead>
<tr>
<th>Variable</th>
<th>Abbreviation</th>
<th>Type</th>
<th>Publisher</th>
</tr>
</thead>
<tbody>
<tr>
<td>Michigan Consumer</td>
<td>MC</td>
<td>Confidence</td>
<td>University of Michigan</td>
</tr>
<tr>
<td>Building Permits</td>
<td>BP</td>
<td>Housing</td>
<td>Census Bureau</td>
</tr>
<tr>
<td>ISM Manufacturing</td>
<td>ISM</td>
<td>Industrial Production</td>
<td>Institute of Supply Management</td>
</tr>
<tr>
<td>Initial Jobless Claims</td>
<td>IJC</td>
<td>Labor</td>
<td>U.S. Department of Labor (DL)</td>
</tr>
<tr>
<td>Personal Spending</td>
<td>PS</td>
<td>Consumer</td>
<td>U.S. Bureau of Economic Analysis (BEA)</td>
</tr>
<tr>
<td>M1 Money Supply</td>
<td>M1</td>
<td>Money Supply</td>
<td>U.S. Federal Reserve (FED)</td>
</tr>
</tbody>
</table>

The motivation behind the choice of the indicators is based upon their ability to measure different parts of the economy and that they are used continuously by professionals. As seen in Table 2 most indicators are published by well-known financial institutions and can be divided into six important aspects of the economy: Confidence, Housing, Industrial Production, Labor, Money Supply and Consumer. Using this categorization we expect to capture reasonable parts of business cycles and the economic development. These aspects have been covered by using the same principles for selecting indicators as is used by the OECD Nilsson (1987). The principles for choosing variables are:

1. Relevance
   - **Economic significance**: In order for an indicator to be chosen, the indicator must have an economic relevance.
   - **Breadth of coverage**: An indicator that covers a broad part of the economy is preferred to an indicator that covers only a small part.

2. Cyclical Behaviour
   - **Cyclical conformity**: Correlated time series cycles provide a guide to further development and possible turning points.
   - **Smoothness**: The cyclical movements in the time series must be distinguishable from noise, i.e. movements without a trend.

3. Practical considerations
   - **Frequency of publication**: Monthly data is preferred over quarterly data
   - **Accessibility**: Availability of time series in terms of easy accessibility
   - **Consistency**: Time series contains no breaks, continuous publication of data

Most of the topics provided above such as *cyclical behaviour* and *practical considerations* are fairly straightforward to apply for all of the indicators in this thesis.
as they are provided by well-known financial institutions and need no further explanation. However the economic significance can be explained further which is done below:

Michigan consumer sentiment index is based on a survey of consumer confidence conducted by the University of Michigan. Consumer confidence is an important aspect of the economy as confident consumers are more likely to e.g. shop, travel, invest and consequently maintain or fuel the economy. The effect is the opposite if the confidence decrease (Baumohl 2012). The housing sector accounts for a large output of the GDP as home-construction businesses accounts for around 5% and if one include complementary services and products such as furniture, carpeting, electronics the sector can account for roughly 20% of the GDP. Thus making the Building permits indicator important to consider. ISM Manufacturing index is based on surveys of more than 300 manufacturing firms and measures the industrial production. Industrial production has a close connection to the business cycle and investors can assume that the stock markets should provide higher returns if the production level increase due to higher corporate profits. Labor market news such as the Initial Jobless Claims (IJC) measuring the amount of people filing for unemployment benefits are important as they provide information about the job market and household earnings (wages from employment is the main source of household income) which can be used to forecast economic output. Note that household spending accounts for approximately 2/3 of the GDP and thereby both IJC and Personal spending are closely monitored by investment professionals (Baumohl 2012). Finally M1 Money supply which is a measurement of the money supply including physical money e.g. coins, checkings and more has exhibited a relationship with GDP and the price level (FED 2016). A summary of the motivation behind the choice of indicators and an explanation of them can be seen in Table 3.

The drawback of using only six indicators is the possibility of an omitted variables bias (OVB), i.e. that there are other indicators that possibly could provide a better fit for the model. This is a common problem in statistics and can be applied for many choices of variables. In general the introduction of more variables will increase the complexity of the problem i.e. it is possible to find more relationships but at the cost of potential biases and a more difficult interpretation of the results. As the indicators are divided into six categories the OVB problem is reduced as indicators within the same categories normally exhibit a very high correlation and describes the same part of the economy. Other indicators within the same category are therefore redundant. An example is the housing sector where indicators such as Building permits, the number of new/old houses sold and housing expectations (NAHB) have a correlation of 90% - 99%. Therefore we do not consider the choice of indicators as a problem but rather we think that the given categories will be able to capture a reasonable part of the economic development.
Table 3: Description of Indicators. In the table below we provide a description of our chosen indicators together with an explanation of what they measure and why it is of importance in the capital markets. Source: U.S. FED/BEA/DL, OECD, ISM, Census Bureau, University of Michigan.

<table>
<thead>
<tr>
<th>Indicator</th>
<th>Explanation</th>
<th>Importance</th>
</tr>
</thead>
<tbody>
<tr>
<td>S&amp;P500</td>
<td>American stock market index on 500 large companies.</td>
<td>Widely considered to be the single best measure of large-cap equities in the US.</td>
</tr>
<tr>
<td>Building Permits</td>
<td>The formal approval by a local jurisdictions prior to the construction of a new or existing building.</td>
<td>As housing indicators account for roughly 5 percent of GDP and an additional 12-13 percent of GDP is accounted by housing services which makes Building permits a very important determinant of the economic output.</td>
</tr>
<tr>
<td>Money Supply M1</td>
<td>All physical money e.g. coins, demand deposits, checking accounts and other deposit accounts.</td>
<td>According to the FED (2016) the money supply has over some time periods exhibited a close relationship with e.g. GDP and the price level. Money supply is therefore an important indicator of the near-term development of the economy and price levels in the long-run.</td>
</tr>
<tr>
<td>Michigan Consumer Sentiment Index</td>
<td>A consumer confidence survey conducted on a monthly by the University of Michigan.</td>
<td>The Michigan Consumer Sentiment builds on the idea that a consumer that is currently happy with their standards of living are more willing and likely to spend more on the economy which should increase economic output.</td>
</tr>
<tr>
<td>Initial Jobless Claims (IJC)</td>
<td>Measures the number of people filing for unemployment benefits. Measures both new and emerging unemployment.</td>
<td>A high number of claims should correlate with a weak economy, as a sustainable increasing IJC level indicates higher unemployment rates which can result in a more challenging economic environment.</td>
</tr>
<tr>
<td>ISM Manufacturing</td>
<td>An index based on surveys of more than 300 manufacturing firms on employment, production inventories, new orders and supplier deliveries.</td>
<td>The capital markets should provide higher returns when the ISM Manufacturing index increases as a result of higher corporate profits. If the indicator is above 50 percent the manufacturing economy is expanding; and vice versa, below 50 percent indicates a contraction (ISM 2016).</td>
</tr>
<tr>
<td>Personal spending</td>
<td>Percentage growth in the amount of money that each household spends in an economy.</td>
<td>Personal spending accounts for approximately 70 percent of the economic activity in the US and therefore is one of the main drivers of growth.</td>
</tr>
</tbody>
</table>
5 Econometric Framework

In this section the econometric framework is described and the model will be derived. First, basic terminology is defined and thereafter the concept of linear regression is defined and the concept of stationary time series is discussed. The econometric model AutoRegressive Distributed Lags (ARDL) is then defined and described. Finally the applied ARDL model is presented including relevant diagnostic tools.

5.1 Terminology

Time series data are data that have been collected over a certain time period (Brooks 2014) i.e. it is a sequence of data points over a time period. An example of a time series is the daily closing value of a stock index collected over a year in chronological order. We may define a time series as $Y = [y_t, y_{t-1}, \ldots, y_0]$ where $y_t$ is the data point at time $t$.

In order to conduct the computational methods proposed later in this section it is important to understand the concept of a lagged value. The lagged value of a time series or rather a data point e.g. $y_t$ is the value of the time series from the previous period i.e. $y_{t-1}$. If a time series is said to have a lag of $p$ the values have shifted $p$ time steps i.e. instead of having the following set of variables $y = [y_t, y_{t-1}, \ldots, y_k]$ we get $\hat{y} = [y_{t-p}, y_{t-p-1}, \ldots, y_{k-p}]$. The change in $y_t$ also termed as the \textit{first difference} is defined by $\Delta y_t = y_t - y_{t-1}$ and is the definition of a short-run change. When the variable is not in first difference i.e. $y_t$ it is said to be in \textit{level form} or simply in \textit{level} and defines the change in the long-run (Brooks 2014). The usage of first difference and the level form of the variables is further explored in Section 5.6. An econometric relationship might be referred to as for instance correlation, dependency or effect. We use the terminology relationship between two or more variables interchangeably as if their values change such that if one variable change so does the value of the other variables.

5.2 Linear Regression

One of the most basic models in econometric work is the linear regression model. The regression model lay the foundation for the more advanced econometric model described in later sections. The model specification is as follows (Brooks 2014):

$$Y = \beta X + \epsilon$$

(5.1)

Where $Y$ and $X$ are vectors of observations e.g. $Y = [y_1, y_2, \ldots, y_n]$ and $X = [x_1, x_2, \ldots, x_t, \ldots, x_n]$. The $\epsilon$ is the vector of residuals of the equation. The $\beta$ is the vector representation of the intercept and slope coefficients. The most common method to find the $\beta$ is the ordinary least squares (OLS) method. The OLS estimate of $\beta$ minimizes the sum of squares of the residuals $\sum \epsilon_i^2 = \hat{\epsilon}^T \hat{\epsilon}$, $\hat{\epsilon} = Y - \hat{\beta}X$. After derivation the estimated slope coefficient that minimizes the residuals sum of squares is the following:

$$\hat{\beta} = (X^T X)^{-1} X^T Y$$

(5.2)
The residual variance $\hat{\sigma}^2$ is defined by $\hat{\sigma}^2 = \frac{(Y - \hat{Y})^T(Y - \hat{Y})}{n}$. The model has some assumptions that need to be met in order for the model to become more robust and to make relevant inference:

1. $\text{E}(\epsilon_t) = 0 \ \forall \ t$. Note: if an intercept is included in the regression equation, this assumption will never be violated (Brooks 2014).
2. $\text{Var}(\epsilon_t) = \sigma^2 < \infty \ \forall \ t$
3. $\text{Cov}(\epsilon_i, \epsilon_j) = 0 \ \forall \ i, j$
4. $\text{Cov}(x_t, \epsilon_t) = 0 \ \forall \ t$
5. $\epsilon \sim \mathcal{N}(0, \sigma^2) \ \forall \ t$

If assumption 1-4 are meet the estimated coefficients including the intercepts are the Best Linear Unbiased Estimators (BLUE) meaning that the OLS estimators are consistent, unbiased and efficient (Brooks 2014). If the last assumption is broken, it may impact inference (hypothesis testing) and render relevant tests useless.

### 5.3 Spurious Regression

In order to conduct a meaningful statistical analysis regardless of the method of choice one may assess the stationarity of the involved time series. Stationarity can according (Brooks 2014) be defined as a time series with a constant mean, constant variance and constant auto-covariances for each given lag i.e. all are constant over time. In general a time series $\{y_t, t \in \mathbb{Z}\}$ is said to be (weakly) stationary if it has the following properties:

1. $\text{Var}(y_t) < \infty$, for all $t \in \mathbb{Z}$
2. $\text{E}[y_t] = u$, for all $t \in \mathbb{Z}$ implying a constant mean.
3. $\text{Cov}(y_r, y_s) = \text{Cov}(y_{r+t}, y_{s+t})$, for all $r, s, t \in \mathbb{Z}$

See Figure 4 and Figure 5 for an example of respective time series.

![Figure 4: Example of a Stationary time series. Source: Authors computation](image1)

![Figure 5: Example of a Non-Stationary time series. Source: Authors computation](image2)

Stationarity or non-stationarity of the underlying time series may have a strong influence of the series behavior and properties and has therefore become an important concept in the field of statistics (Brooks 2014). A famous fallacy of the usage of non-stationary data in statistics is a concept called spurious regression which refers to the phenomenon of receiving a relationship in a regression between two variables despite that they are independent. Often these regression have misleading significant coefficient estimates and a deceptive high goodness of fit ($R^2$). For
example if one perform a regression between two independent stationary variables it is expected that the slope coefficient should be close to zero and $R^2$ to be low. However if the times series are non-stationary it is possible that the regression may provide a high $R^2$ even though the variables have no connection. Thereby if one conduct a regression on non-stationary data one may obtain good looking but useless results (Brooks 2014).

Financial time series such as the daily closing prices of S&P500 are often non-stationary in level but the first difference i.e. the growth rate is often stationary. A non-stationary time series $y_t$ that is stationary in first difference is said to be integrated of order one and is denoted by $I(1)$. In general if a non-stationary series must be differenced $d$ times before becoming stationary the series is said to be integrated of order $d$ and is denoted by $I(d)$. Note that if the series is stationary at level e.g. $y_t$ (non-differenced) it is denoted by $I(0)$ (Brooks 2014).

5.4 Long-run Relationship

The property of non-stationarity of a time series does not make it useless for analysis and relationship assessment with other non-stationary variables. This could be explained by the fact that non-stationary series may have similar trend and seasonality components over a time period due to e.g. economic interrelations which form a relationship in the long-run. This phenomenon is termed cointegration and is according to Brooks (2014) a long-term or equilibrium relationship as cointegrated variables may deviate from each other in the short-run, but the association among the variables is present in the long-run (see Figure 6). Accordingly the series will move jointly and if pairs of variables are cointegrated it implies that they have similar stochastic trends.

From a mathematical perspective cointegration has the following definition (Brooks 2014): Let $m_t$ be a $k \times 1$ vector of variables, then the components of $m_t$ are integrated of order $(d,b)$ and cointegrated if:

1. All components in $m_t$ are $I(d)$
2. There exist at least one coefficient vector $\beta \neq \vec{0}$ such that $\beta m_t \sim I(d-b)$

To simplify, two or more non-stationary variables ($m_t$) are said to be cointegrated if a linear combination of the variables ($\beta m_t$) are stationary and mean-reverting. As the linear combination becomes stationary one may avoid spurious regression. Due to the statistical properties, cointegration may only be possible between variables of the same integration order. According to Brooks (2014) economic theory often suggests that cointegration should exist between some financial variables. Common examples where cointegration might exist is between spot and futures prices for a given commodity/asset and between equity prices and dividends.

To summarize, cointegration allows a linear combination of non-stationary variables to become stationary and have a long-run relationship. An example of two cointegrated series can be seen in Figure 6.
5.5 Augmented Dickey-Fuller Test

To test the time series data for stationarity a common method is to apply an Augmented Dickey-Fuller test (ADF) (Dickey & Fuller 1979, Brooks 2014) to test for a unit root. A time series with a unit root is said to be non-stationary. There are other common methods for determining the stationary of a variable such as the Phillips-Perron (PP) test. The test are similar to the ADF test but with a few alternations in order to allow for autocorrelated residuals. However the tests often provide similar conclusions (Brooks 2014) and we therefore consider the ADF test as sufficient enough for our purpose.

The ADF test is a regression analysis based on equation 5.3 where $\beta$ is a constant, $p$ the chosen lag, $\phi$ and $\alpha$ the coefficients of the regression, $\lambda t$ is a trend term and $u_t$ is the white noise. Note that if $\lambda t = \beta = 0$ the equation is modeling a unit root test without trend and drift while if only $\lambda t = 0$ the equation is a model with drift. The final possible case is if there exists no constraints, then the test tries to assess if $y_t$ has a unit root with drift and a deterministic time trend.

$$\Delta y_t = \beta + \lambda t + \phi y_{t-1} + \sum_{i=1}^{p} \alpha_i \Delta y_{t-i} + u_t$$

The unit root test is then conducted by investigating the following hypothesis test:

$H_0 : \phi = 0$, unit root is present i.e. the time series is non-stationary

$H_1 : \phi < 0$, no unit root is present i.e. the time series is stationary

The test statistic is defined by $\hat{\phi} / SD(\hat{\phi})$, where $\hat{\phi}$ is the estimated values from equation 5.3 and $SE(\hat{\phi})$ is the standard error of the estimate. The test statistic do not follow the regular t-distribution under the null hypothesis, rather the statistic follows a non-standard distribution and the critical values for this test have been derived by simulation. Critical values for the ADF test can be found in (Fuller 1976) and can be interpolated for different lags. The basis for the ADF test is to conclude if the time series is non-stationary by estimating if the past values $y_{t-1}$ may explain the change ($\Delta y_t = y_t - y_{t-1}$) in the current value $y_t$.

Furthermore as the choice of the lag $p$ affect the model it is important to deter-
mine the optimal lag (Brooks 2014). There exist several methods for determining the optimal lag length $p$ and a common method is to minimize the value of an information criteria using the AIC (Akaike 1974) and/or the Schwarz-Bayesian (SIC) (Schwarz et al. 1978) criteria defined by equation 5.4 and equation 5.5.

$$\text{AIC} = -2\ln(LH) + 2k \quad (5.4)$$

$$\text{SIC} = -2\ln(LH) + k\ln(n) \quad (5.5)$$

The variable $n$ is the number of observations and $k$ is the number of regression parameters to be estimated partly defined by the lag $p$ (see equation 5.3. $\alpha_i, \phi$). LH is the maximum likelihood of the model. According to Brooks (2014) no criteria is superior to another. However, as discussed in Section 5.7.1 the Schwarz-Bayesian criteria is preferred for our model of choice ARDL, hence to be consistent we choose to apply SIC.

The lag length may also be chosen by analyzing the frequency of the data. Monthly data may have a lag length of 12, quarterly 4 and yearly 2 (Brooks 2014). However to be consistent the SIC criteria is used, while the explained frequency criteria is only used to determine the upper limit (the maximum) of the lag included in the model.

### 5.6 Autoregressive Distributed Lags

To assess the short-run and long-run relationship between the macroeconomic indicators and the stock market the Autoregressive Distributed Lags (ARDL) method is utilized. The ARDL method was introduced and developed by Pesaran & Shin (1998) and was refined a few years later by Pesaran et al. (2001). The ARDL method has been extensively utilized as it provides several advantages over traditional statistical methods for assessment of cointegration and short/long-run relationships.

Firstly, in contrast to traditional methods such as Johansen’s tests (Johansen 1991), Granger/Enger causality test (Engle & Granger 1987) and Vector Autoregression (VAR), ARDL can be utilized to test for a level relationship for variables that are either $I(0)$ or $I(1)$ as well as for a mix of $I(0)$ and $I(1)$ variables (Duaasa 2007, Adom et al. 2012). However ARDL does not work with non-stationary variables integrated of order two $I(2)$. The possibility to combine $I(0)$ and $I(1)$ variables is a great advantage as financial times series often are either $I(1)$ or $I(0)$. The advantage can be further clarified by comparing e.g. VAR with ARDL. If one would conduct a VAR approach the series are required to be stationary and if the data is non-stationary $I(1)$ one would have to take the first difference of the series ($\Delta y_t$) and then utilize VAR. However if one take the first difference of the data, long-run relations between series may disappear (Brooks 2014). In contrast, in an ARDL framework it is not necessary to make an adjustment to the data and hence long-run relationships still remain possible to calculate.
Additionally the ARDL method integrates the short-run impact of the given variables with a long-run equilibrium defined in Section 5.6.1 using an error correction term without dropping long-run information. Accordingly one may assess the short-run and long-run relationship between the given variables simultaneously. Furthermore unlike traditional cointegration tests, it’s possible to determine different lags for each variable in the model (Pesaran et al. 2001) which makes it more flexible. Lastly, most cointegration techniques are sensitive to the sample size while the ARDL method provides robust and consistent results for small sample sizes (Pesaran & Shin 1998, Pesaran et al. 2001, Adom et al. 2012) which is good for our setting as we have sample sizes ranging from 80-190.

Due to the proposed econometric advantages the ARDL method was utilized in this thesis to assess long-run and short-run relationship between macroeconomic indicators and the stock market.

5.6.1 Model Specification

When analyzing possible relationships between two or more variables the researcher often postulate specifications according to e.g. equation 5.6, where \( Y \) is the dependent variable and \( X \) is a vector of independent variables and \( f \) is some function.

\[
Y = f(X) \tag{5.6}
\]

The ARDL model procedure introduced by Pesaran et al. (2001) is a model that tries to capture the relationship in \( f(X) \). In this section the ARDL model will be clarified by describing the most simple version of ARDL i.e. a one variable \( ARDL(q,p) \) model and in the next section the model is applied to the variables of choice in this thesis.

Following the work by Pesaran & Shin (1998) and Pesaran et al. (2001), the \( ARDL(q,p) \) model of equation 5.6 can be specified by equation 5.7 where \( y_t \) is the dependent variable and \( x_t \) is the independent variable and \( q, p \) are the respective lags.

\[
\Delta y_t = \beta_0 + C_0 t + \sum_{i=1}^{q} \varsigma_i \Delta y_{t-i} + \sum_{j=0}^{p} \omega_j \Delta x_{t-j} + \gamma_1 y_{t-1} + \gamma_2 x_{t-1} + \epsilon_t \tag{5.7}
\]

The coefficients \( \beta_0, C_0 \) are the drift and trend coefficients respectively and \( \epsilon_t \) is the white noise error. The coefficients \( \varsigma_j \) and \( \omega_j \) for all \( j \) corresponds to the short-run relationship while the \( \gamma_j, j = 1, 2 \) corresponds to the long-run relationship.

As the model tries to capture the long-run relationship between the variables we have to define what a long-run relationship means in the context of the ARDL model. The definition of a long-run relationship that is commonly employed in econometrics is that the variables converge to some long-term values and are no longer changing dramatically (Brooks 2014). Hence in the long-run equilibrium the system is stable implying that the states of the system remain constant over a period of time and there is no tendency for change i.e. \( y_t = y_{t-1} = y; x_t = x_{t-1} = x \).
This implies that if an equilibrium exist the first differenced variables denoted in equation 5.7 will be zero in the long-run equilibrium. To clarify, as the model is assumed to converge to an equilibrium, the first differenced variables are zero i.e. \(\Delta y_{t-i} = \Delta x_{t-j} = 0\ \forall\ i, j\) in the long-run (Brooks 2014). The assumption is fairly common in macroeconomics and a common example is the dynamic between quantity and price in a supply-demand diagram as in equilibrium neither the quantity or the supply is moving i.e. there is no growth in either direction. Thus in the long-run, the one variable case equation 5.7 becomes:

\[
\gamma_1 y_{t-1} + \gamma_2 x_{t-1} + \epsilon_t + \beta_0 + C_0 t = 0
\]  

(5.8)

Hence the final long-run coefficient for \(x\) is \(-\frac{\gamma_2}{\gamma_1}\).

Given that equation 5.7 has been proposed the continued process in the ARDL approach can be divided into three key steps. The first step is to estimate equation 5.7 in order to conduct a F-bounds test for a long-run relationship between the variables.

### 5.6.2 F-Bounds Test and Error Correction Modelling

Using the results from equation 5.7 it is possible to determine if a long-run relationship exists among the variables. To establish if a long-run relationship exist, an F-test is performed. The test involves computing equation 5.7 and analyze if the coefficients for the one period lagged variables i.e. \(\gamma_1\) and \(\gamma_2\) are jointly zero. Thus the following hypothesis test is performed:

\[
H_0 : \gamma_1 = \gamma_2 = 0: \text{A Long-run relationship does not exist}
\]
\[
H_1 : \gamma_1 \neq 0 \cup \gamma_2 \neq 0: \text{A Long-run relationship exist}
\]

The F-test in the ARDL framework has a non-standard distribution that depends on:

1. The mix of \(I(0)\) and \(I(1)\) independent variables.
2. The number of independent variables
3. If the model includes an intercept and/or trend term

Thus the hypothesis test is not similar to regular hypothesis testing rather it involves both upper and lower bounds of critical values and the test has three different cases. To be able to reject or fail to reject the null hypothesis, one has to consider the critical values tabulated in Pesaran et al. (2001). If the computed F-statistic is greater than the upper bound the null hypothesis is rejected and the existence of a long-run (level) relationship between the variables regardless of the order of integration of the variables is evident (Duasa 2007). If the F-statistic falls below the lower bound the null hypothesis cannot be rejected and the presence of cointegration is not significant. Finally if the F-statistic fall in between the upper and lower bound the test is inconclusive and additional information is needed before a conclusion can be made (Pesaran et al. 2001):

\[
\text{Fail to Reject } H_0 < \text{Inconclusive} < \text{Reject } H_0
\]  

(5.9)
When the test provides inconclusive results a possible remedy can be to examine
the error correction term following the work by Banerjee et al. (1998) and Kre-
used a negative and significant ECM-term in a similar framework to motivate
cointegration and long-run relationship under the inconclusive case. An equiv-
alent test that can be performed to assess the cointegration of the variables is
the t-test which has a similar approach as above i.e. the usage of a similar null
hypothesis and lower and upper bounds which are presented by (Pesaran et al.
2001). The t-test can be used as a complementary test if the F-test is inconclusive.

To define a ECM-term, which is the second step in the ARDL approach a few
assumptions have to be made. Given that the F-bound test produce satisfactory
results it is possible to determine the long-run equilibrium relationship without
spurious regression as the linear combination of the non-stationary variables are
stationary in a simple OLS framework:

\[ y_t = \beta_0 + \beta_1 x_t + \epsilon_t. \]  (5.10)

To capture the convergence of the model towards equilibrium an error correction
term is defined by \( ECM_{t-1} = y_{t-1} - \hat{\beta}_0 - \hat{\beta}_1 x_{t-1} \) where \( \hat{\beta} \)'s are the estimators from
equation 5.10. Note that \( ECM_{t-1} \) is the residuals from equation 5.10. Furthermore
if the model is moving towards equilibrium in the long-run the difference between
the independent and dependent variables \( ECM_{t-1} \) cannot increase as that would
impose divergence. Hence the difference must decrease. Furthermore as \( x_t, y_t, \beta_j \)
are all given from the regression in equation 5.10, \( ECM_{t-1} \) becomes a new data
series. In the final and third step, the short-run dynamics are estimated by using
equation 5.7 by replacing the lagged variables \( y_t, x_t \) with the error correction term
\( ECM_{t-1} \). The equation can be specified as follows:

\[
\Delta y_t = \beta_0 + C_0 t + \sum_{i=1}^{q} \varsigma_i \Delta y_{t-i} + \sum_{j=0}^{p} \omega_j \Delta x_{t-j} + \lambda ECM_{t-1} + \epsilon_t \]  \hspace{1cm} (5.11)

The ECM coefficient \( \lambda \) must be statistically significant and negative in order for
the model to converge to equilibrium. Furthermore a significant ECM coefficient
confirms the existence of a stable long-run relationship and cointegration between
the independent and dependent variables. The coefficient also determine the speed
of adjustment towards equilibrium, for instance, assume we have annual data and
\( \lambda = -0.5 \). Then \( y \) will after a shock in \( x \) return to equilibrium in the long-run
with a speed of 50% per year. The ECM term is very useful for many practitioners
including policy makers e.g. ECB as they can analyze how fast their policies
impact the economy.
5.7 Application of ARDL

In this section the ARDL model is applied to our data and the general equation is presented and explained. The lag selection necessary in order to obtain good results is described as well as the specific F-bound test.

In this thesis we want to capture the long-run and short-run dynamics between the macroeconomic indicators in Table 2 and the US stock market index S&P500. S&P500 is denoted as SP500 in the equations. All data is expressed as the natural logarithms except personal spending as it is in percentage form. The logarithm is taken in order to ease the interpretation of the results and to reduce possible heteroscedasticity. Following the description above and equation 5.12 the applied ARDL model is given in equation 5.12.

\[
\Delta \ln(SP500)_t = \beta_0 + \sum_{i=1}^{p_0} v_i \Delta \ln(SP500)_{t-i} + \sum_{i=0}^{p_1} \tau_i \Delta \ln(BP)_{t-i} + \\
\sum_{i=0}^{p_2} \theta_i \Delta \ln(IJC)_{t-i} + \sum_{i=0}^{p_3} \varphi_i \Delta \ln(MC)_{t-i} + \\
\sum_{i=0}^{p_4} \nu_i \Delta \ln(M1)_{t-i} + \sum_{i=0}^{p_5} \varphi_i \Delta \ln(MC)_{t-i} + \\
\sum_{i=0}^{p_6} \delta_i \Delta \ln(ISM)_{t-i} + \eta_0 \ln(SP500)_{t-1} + \\
\eta_1 \ln(BP)_{t-1} + \eta_2 \ln(IJC)_{t-1} + \eta_3 \ln(MC)_{t-1} + \\
\eta_4 \ln(M1)_{t-1} + \eta_5 \ln(ISM)_{t-1} + \\
\rho D_{ISM>50} + \epsilon_t
\]  

Where \( p_j, \forall j \) are the chosen lags, \( \beta_0 \) is the intercept, \( C_0 \) is the trend coefficient and \( \epsilon \) is the white noise. The remaining coefficients describe short-run and long-run relationships. The \( \eta_j, j = 0, 1, \ldots, 6 \) correspond to the long-run relationship while the short-run effects are captured by the coefficients for the first difference variables i.e. \( v_i, \tau_i, \theta_i, \varphi_i, \delta_i, \forall i \). As mentioned in Table 3 the ISM Manufacturing index indicates increased industrial activity if it is above 50 and a contraction if the index is below 50. To assess if that limit is relevant we introduce the exogenous dummy variable \( D_{ism>50} \) which is one when ISM is above 50 and zero when below 50.

The corresponding error correction equation can be seen in equation 5.13. The importance of each of the variables will be determined from the perspective of significance rather than from the magnitude of the coefficients or the p-value. This implies that if the variables are found to have an explainable relationship with the stock market they are considered to be important.
\[
\Delta \ln(\text{SP500})_t = \beta_0 + \sum_{i=1}^{p_0} v_i \Delta \ln(\text{SP500})_{t-i} + \sum_{i=0}^{p_1} \tau_i \Delta \ln(BP)_{t-i} + \\
\sum_{i=0}^{p_2} \theta_i \Delta \ln(IJC)_{t-i} + \sum_{i=0}^{p_3} \phi_i \Delta PS_{t-i} + \\
\sum_{i=0}^{p_4} \nu_i \Delta \ln(M1)_{t-i} + \sum_{i=0}^{p_5} \varphi_i \Delta \ln(MC)_{t-i} + \\
\sum_{i=0}^{p_6} \delta_i \Delta \ln(ISM)_{t-i} + \lambda ECM_{t-1} + \rho D_{ISM>50} + \epsilon_t
\]

(5.13)

5.7.1 Lag Selection

Similar to the ADF test in Section 5.5 the lag selection is important as it determines the results of the model (see equation 5.12). As mentioned in Section 5.5 one can use several methods to obtain the optimal lag for each variable. However the SIC criteria provides slightly better estimates than the AIC criteria in small samples in the ARDL framework (Pesaran & Shin 1998). The AIC criteria also tends to overestimate the number of lags to be included, which is not favorable in small samples as by increasing the lag the number of observations decrease. Thus in order to establish a coherent model the SIC criteria will be used to govern the lag length for both the ADF test as well as for the ARDL model. However as noted by Pesaran et al. (2001) serial correlation as well as heteroskedasticity, misspecification and non-normality should not be present, hence the lag length should be adjusted for the possible biases.

5.7.2 F-bound Test

To test if the variables have a long-run relationship, the F-test will be performed. The test involves computing equation 5.12 and analyze if the coefficients for the one period lagged variables i.e. \( \eta_j, j = 0, 1, 2, 6 \) are jointly zero. Thus the following hypothesis test will be performed:

\[
H_0 : \eta_j = 0 \forall j: \text{A Long-run relationship does not exist} \\
H_1 : \eta_j \neq 0 \text{ for some } j: \text{A Long-run relationships exist}
\]

An hypothesis test for each long-run coefficient will also be conducted to evaluate which of the indicators that have a significant relationship. As done in previous research, to reject or fail to reject the null hypothesis, the critical values tabulated in Pesaran et al. (2001) will be utilized. If the F-statistic falls above the critical value we assume that there is a long-run relationship between the variables. If it falls below we reject the notion of a long-run relationship and if it is in between we utilize the t-statistic or any other pre-mentioned method in Section 5.6.2.
5.8 Diagnostic Testing

The ARDL model tries to find the best linear unbiased estimator (BLUE) and thereby diagnostic tests need to be conducted. As many other research papers such as Tian & Ma (2010) and Hasan & Nasir (2008) we will further validate the results and ensure that the results are statistically robust by utilizing tests for stability, serial correlation, heteroscedasticity, misspecification (RESET) and normality in the residuals. If the model contains none of the below biases and the model provides satisfactory results in accordance with Section 5.6.1 we are satisfied with the results and we can conclude that the results can be used for analysis.

5.8.1 Test for Stability

The ARDL model is quite sensitive to structural breaks and as we are using financial time series that are sensitive to worldwide events the stability of the coefficients needs to be analyzed. To assess the stability of the long-run and short-run coefficients CUSUM and CUSUMSQ tests proposed by Brown et al. (1975) can be used. If there is instability in the coefficients one may increase the sample size or introduce dummy variables (Naiya & Manap 2013, Juselius 2006, Fuinhas & Marques 2012).

The tests are based on the cumulative sum of the recursive residuals (CUSUM) and the cumulative sum of squared recursive residuals (CUSUMSQ) and are of a graphical nature whereby the residuals are updated recursively and are plotted against the break points for the 5% significance line. Figure 7 illustrates the concept of the CUSUM test where the cumulative sum of recursive residuals are plotted against the upper and lower 95% confidence bounds. The concept remains the same for CUSUMSQ. The long-run and short-run coefficients are stable if the plot of CUSUMSQ and CUSUM stay within the 5% significance level. In detail both tests analyze if the residuals do not significantly deviate from its mean value by imposing parallel critical lines on a 5% significance level.

![Figure 7: Example of CUSUM test. Source: Authors computation](image-url)
5.8.2 Test for Serial Correlation

Breusch-Godfrey test (Godfrey 1978) for serial correlation if different lags of the residuals are correlated. Mathematically the following should hold true: Covariance $(\epsilon_i, \epsilon_j) = 0, \forall i, j$ otherwise the series has serial correlation. Serial correlation does not affect the unbiasedness of the regression estimators but rather affect the efficiency i.e. the estimators are not BLUE (Brooks 2014). It may for example affect the standard errors of the regression which invalidate significance tests i.e. there is a possibility that wrong inferences could be made whether the independent variables are determinants of the variations in the dependent variable. The model of the residuals under the simplest form of the Breusch-Godfrey test is:

$$\epsilon_t = \epsilon_{t-1} \rho + v_t, \quad v_t \sim N(0, \sigma_v^2)$$

(5.14)

The test has the following general null hypothesis and alternative hypothesis:

- $H_0$: $\rho = 0$, No serial correlation in the model
- $H_1$: $\rho \neq 0$, There is serial correlation in the model

5.8.3 Test for Heteroscedasticity

Test that all residuals have a constant variance i.e. $\text{Variance}(\epsilon_t) = \sigma^2 < \infty, \forall t$. In the regular OLS estimation as well as for the ARDL model it is assumed that the residuals have a constant variance (homoscedasticity). If the model does not have a constant variance (heteroscedasticity) in the residuals the estimated coefficients will no longer be BLUE and will not have the minimum variance of the unbiased estimators. In relation to serial correlation the consequence could be that one make wrong inferences. In this thesis we will use Whit's test for heteroscedasticity (White 1980) which has the following very general null and alternative hypothesis:

- $H_0$: Constant variance of the residuals - Homoscedasticity
- $H_1$: Non-constant variance of the residuals - Heteroscedasticity

5.8.4 Regression Specification Error Test

Ramsey Regression Specification Error Test (RESET) (Ramsey 1969) for functional form i.e. it tests if non-linear combinations of the fitted values can describe the explanatory variable. If non-linear combinations of the fitted values have power in describing the explanatory variable the model is said to be misspecified and needs adjustments. Mathematically if one utilize OLS on $y_t = \beta_0 + \beta_1 x_t + \epsilon_t$ and $\hat{y}_t = \hat{\beta}_0 + \hat{\beta}_1 x_t$ is the fitted values then the RESET test, tests if $\hat{y}_t^2, \hat{y}_t^3, \ldots, \hat{y}_t^l$ have explanatory power on $y_t$ in $y_t = \beta_0 + \beta_1 x_t + \beta_2 \hat{y}_t^2 + \beta_3 \hat{y}_t^3 + \ldots + \beta_l \hat{y}_t^l + \epsilon_t$ (Brooks 2014). The non-mathematical null and alternative hypothesis is as follows:

- $H_0$: No power in non-linear combinations - No misspecification
- $H_1$: The non-linear combinations have power - Misspecification
5.8.5 Test for Normality of the Residuals

The Jarque-Bera test for normality in the residuals i.e. if $\epsilon_t \sim N(0, \sigma^2), \forall t$. The assumption that $\epsilon_t \sim N(0, \sigma^2), \forall t$ is necessary in order to conduct hypothesis tests of model parameters. Thus non-normality may cause problems regarding statistical inference of the coefficient estimates such as significance tests and for confidence intervals that relies on the normality assumption (Brooks 2014). The very general null and alternative hypothesis are as follows:

$$H_0: \text{There is normality in the residuals}$$
$$H_1: \text{There is non-normality in the residuals}$$

5.8.6 Economic Significance

Given that the results are non-biased in terms of the above fallacies, one more robustness check have to be made. As the study covers the relationship between macroeconomic indicators and the stock market index S&P500 i.e. financial time series are used the economic significance or the plausibility of the results should be discussed. Following Brooks (2014) with a slight adjustment for our research and already mentioned biases the following non-mathematical criteria should be satisfied for an acceptable model:

- The results should be logically plausible
- The results should be consistent with macroeconomic theory

In order to satisfy the criteria and determine if the results are relevant from a macroeconomic perspective we will dedicate an entire Section (7) to discuss the findings and conclude if the results are relevant.

5.9 Summary of Econometric Framework

To investigate the short-run and long-run relationship between macroeconomic variables and S&P500 the ARDL model is used. The method of choice can be summarized in the following steps:

1. **Unit root test**: As the ARDL does not work with $I(2)$ variables, one has to investigate if the given time series are $I(0)$ and/or $I(1)$. To investigate the stationarity the ADF test described in Section 5.5 will be used. If the given time series are either $I(0)$ or $I(1)$ we can continue with our procedure.
2. **Lag selection**: Select the optimal lag for the ARDL model using the SIC criteria and adjust for possible biases.
3. **Computations**: Run the ARDL model in accordance with equation 5.12.
4. **F-Bounds test**: Evaluate if cointegration is present in the time series and the existance of long-run relationship between the macroeconomic variables and S&P500.
5. **Estimate coefficients**: Calculate the short-run and long-run coefficients including the ECM term.
6. **Validity test**: Validate the results by investigating if they are biased by amongst other things serial correlation and heteroscedasticity.

7. **Stability test**: Test if the estimated coefficients are stable which would confirm that long-run relationships exist.

8. **Analysis of results**: Analyze the results in order to determine if they are logically plausible.
6 Results

In this section we present the results from the ADF-test and ARDL model described in Section 5.5-5.7. The structure of this chapter follows the guideline in Section 5.9. First the ADF results for all time periods are presented and then the ARDL model is utilized on each of the given time periods.

The aforementioned periods will be analyzed separately since there are some different underlying characteristics of the market during each of the considered time periods. As the periods may have different characteristics, each time period may induce different types of biases and related problems that need to be evaluated. Biases in the sample during each time period could be corrected by e.g. increasing the sample size however this will not be possible as the time periods are fixed. Therefore there might be different conclusions and remedies for certain problems in all periods. These remedies and methodologies will be presented and if it is not necessary to make any adjustments one may assume that the analysis follows the step-by-step structure in Section 5.9.

6.1 Stationary or Non-Stationary Data

The ARDL model works for a mixture of variables that are stationary in level, i.e. $I(0)$ or in first difference, i.e. $I(1)$ but the variables cannot be of order $I(2)$ or higher. To test the order of integration of the variables the ADF-test described in Section 5.5 is conducted. The test is performed on the time series both in level and differenced forms. Furthermore to assure there is no $I(2)$ variable the ADF-test is utilized both with a trend and without a trend i.e. with and without the $\lambda$ in equation 5.3. There is a possibility that some variables may exhibit stationarity only when we adjust for the trend which will provide further information and is general robustness check for our data. Furthermore the lag selection is based on the SIC criteria described in Section 5.5.

6.1.1 ADF-Tests

The results can be seen in Table 4-6 where the test-statistic, the p-value and the selected lag structure are presented. Period 1, period 1a and period 1b represents the time periods around 2000-2016, 2000-2009 and 2009-2016 respectively. The presented p-values are the MacKinnon p-values and critical values for the ADF-test can be seen in Table 7. The significance level of interest is set to 0.05, 0.025, 0.01 (5%, 2.5%, 1%) for a more conservative analysis, however the 10% critical values for the ADF test are shown for reference. The ”Conclusion” column to the right in Table 4-6 provides the general conclusion of the test i.e. the order of integration of a certain variable.

As seen in the Tables 4-6 some of the variables are either $I(0)$ or $I(1)$ depending whether a trend term is used or not. For example, Michigan Consumer in Table 4 is $I(0)$ with no trend and $I(1)$ with a trend. This highlights the advantage of using the ARDL model as the model in contrast to other similar models such as Johansen’s test can be used as long as the variables are either $I(0)$ or $I(1)$. Therefore the mix of integration is not a problem and no further analysis from
this perspective have to be done. In general all the variables are either $I(0)$ or $I(1)$ regardless of time period which implies that the ARDL model can be used and we can continue with the calculations. The same conclusion can be drawn by a visual inspection of Figure 34-36 in Appendix B.2.

Table 4: ADF test for period 1. ***,*** represents a significance level of 5%, 2.5% and 1% respectively. SIC is the optimal lag. The values in parenthesis are the MacKinnon p-values and the remaining numbers are the test-statistics. Source: Authors computation

<table>
<thead>
<tr>
<th>Variables</th>
<th>SIC</th>
<th>ADF - No Trend</th>
<th>ADF - Trend</th>
<th>SIC</th>
<th>ADF - No Trend</th>
<th>ADF - Trend</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>SP500</td>
<td>1</td>
<td>0.803 (0.818)</td>
<td>-1.923 (0.663)</td>
<td>0</td>
<td>-12.482 (0.000)</td>
<td>-12.582 (0.000)</td>
<td>$I(1)$***</td>
</tr>
<tr>
<td>ISM Manufacturing</td>
<td>3</td>
<td>-3.657 (0.005)</td>
<td>-3.771 (0.018)</td>
<td>0</td>
<td>-11.449 (0.000)</td>
<td>-11.419 (0.000)</td>
<td>$I(0)$***</td>
</tr>
<tr>
<td>Michigan Consumer</td>
<td>1</td>
<td>-2.886 (0.047)</td>
<td>-2.779 (0.265)</td>
<td>0</td>
<td>-13.663 (0.000)</td>
<td>-13.688 (0.000)</td>
<td>$I(0)$<em>/$I(1)$</em>**</td>
</tr>
<tr>
<td>LJC</td>
<td>2</td>
<td>-1.770 (0.395)</td>
<td>-1.871 (0.669)</td>
<td>1</td>
<td>-11.258 (0.000)</td>
<td>-11.432 (0.000)</td>
<td>$I(1)$***</td>
</tr>
<tr>
<td>Building Permits</td>
<td>1</td>
<td>-0.921 (0.781)</td>
<td>-0.486 (0.984)</td>
<td>0</td>
<td>-15.108 (0.000)</td>
<td>-15.118 (0.000)</td>
<td>$I(1)$***</td>
</tr>
<tr>
<td>Personal Spending</td>
<td>0</td>
<td>-14.82 (0.000)</td>
<td>-15.15 (0.000)</td>
<td>4</td>
<td>-10.323 (0.000)</td>
<td>-10.290 (0.000)</td>
<td>$I(0)$***</td>
</tr>
<tr>
<td>M1</td>
<td>4</td>
<td>1.7440 (0.998)</td>
<td>-0.899 (0.956)</td>
<td>3</td>
<td>-5.7440 (0.000)</td>
<td>-6.1760 (0.000)</td>
<td>$I(1)$***</td>
</tr>
</tbody>
</table>

Table 5: ADF test for period 1a. ***,*** represents a significance level of 5%, 2.5% and 1% respectively. SIC is the optimal lag. The values in parenthesis are the MacKinnon p-values and the remaining numbers are the test-statistics. Source: Authors computation

<table>
<thead>
<tr>
<th>Variables</th>
<th>SIC</th>
<th>ADF - No Trend</th>
<th>ADF - Trend</th>
<th>SIC</th>
<th>ADF - No Trend</th>
<th>ADF - Trend</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>SP500</td>
<td>4</td>
<td>-1.165 (0.688)</td>
<td>-0.937 (0.952)</td>
<td>3</td>
<td>-3.394 (0.011)</td>
<td>-3.448 (0.045)</td>
<td>$I(1)$***</td>
</tr>
<tr>
<td>ISM Manufacturing</td>
<td>1</td>
<td>-1.075 (0.725)</td>
<td>-1.053 (0.937)</td>
<td>0</td>
<td>-8.675 (0.000)</td>
<td>-8.718 (0.000)</td>
<td>$I(1)$***</td>
</tr>
<tr>
<td>Michigan Consumer</td>
<td>1</td>
<td>-1.143 (0.698)</td>
<td>-2.192 (0.494)</td>
<td>0</td>
<td>-10.636 (0.000)</td>
<td>-10.613 (0.000)</td>
<td>$I(1)$***</td>
</tr>
<tr>
<td>LJC</td>
<td>1</td>
<td>-0.445 (0.902)</td>
<td>-0.441 (0.986)</td>
<td>0</td>
<td>-11.914 (0.000)</td>
<td>-11.946 (0.000)</td>
<td>$I(1)$***</td>
</tr>
<tr>
<td>Building Permits</td>
<td>1</td>
<td>3.528 (1.000)</td>
<td>2.320 (1.000)</td>
<td>0</td>
<td>-10.695 (0.000)</td>
<td>-12.057 (0.000)</td>
<td>$I(1)$***</td>
</tr>
<tr>
<td>Personal Spending</td>
<td>0</td>
<td>-11.179 (0.000)</td>
<td>-11.685 (0.000)</td>
<td>3</td>
<td>-8.488 (0.000)</td>
<td>-8.494 (0.000)</td>
<td>$I(0)$***</td>
</tr>
<tr>
<td>M1</td>
<td>4</td>
<td>-0.725 (0.840)</td>
<td>-19.67 (0.620)</td>
<td>3</td>
<td>-4.335 (0.000)</td>
<td>-4.284 (0.000)</td>
<td>$I(1)$***</td>
</tr>
</tbody>
</table>

Table 6: ADF test for period 1b. ***,*** represents a significance level of 5%, 2.5% and 1% respectively. SIC is the optimal lag. The values in parenthesis are the MacKinnon p-values and the remaining numbers are the test-statistics. Source: Authors computation

<table>
<thead>
<tr>
<th>Variables</th>
<th>SIC</th>
<th>ADF - No Trend</th>
<th>ADF - Trend</th>
<th>SIC</th>
<th>ADF - No Trend</th>
<th>ADF - Trend</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>SP500</td>
<td>1</td>
<td>-1.594 (0.487)</td>
<td>-3.385 (0.053)</td>
<td>0</td>
<td>-10.664 (0.000)</td>
<td>-10.671 (0.000)</td>
<td>$I(1)$***</td>
</tr>
<tr>
<td>ISM Manufacturing</td>
<td>1</td>
<td>-4.707 (0.000)</td>
<td>-4.864 (0.000)</td>
<td>0</td>
<td>-7.997 (0.000)</td>
<td>-8.269 (0.000)</td>
<td>$I(0)$***</td>
</tr>
<tr>
<td>Michigan Consumer</td>
<td>1</td>
<td>-2.074 (0.255)</td>
<td>-3.777 (0.018)</td>
<td>0</td>
<td>-8.787 (0.000)</td>
<td>-8.702 (0.000)</td>
<td>$I(1)$***</td>
</tr>
<tr>
<td>LJC</td>
<td>3</td>
<td>-2.236 (0.193)</td>
<td>-4.155 (0.005)</td>
<td>2</td>
<td>-6.785 (0.000)</td>
<td>-6.996 (0.000)</td>
<td>$I(1)$*** $I(0)$***</td>
</tr>
<tr>
<td>Building Permits</td>
<td>2</td>
<td>-0.794 (0.821)</td>
<td>-1.933 (0.637)</td>
<td>1</td>
<td>-7.564 (0.000)</td>
<td>-7.515 (0.000)</td>
<td>$I(1)$***</td>
</tr>
<tr>
<td>Personal Spending</td>
<td>0</td>
<td>-1.504 (0.000)</td>
<td>-10.429 (0.000)</td>
<td>2</td>
<td>-8.787 (0.000)</td>
<td>-8.729 (0.000)</td>
<td>$I(0)$***</td>
</tr>
<tr>
<td>M1</td>
<td>1</td>
<td>-0.837 (0.808)</td>
<td>-1.154 (0.919)</td>
<td>0</td>
<td>-10.012 (0.000)</td>
<td>-10.003 (0.000)</td>
<td>$I(1)$***</td>
</tr>
</tbody>
</table>

Table 7: ADF Critical Values. Source: Fuller (1976), Authors Computations

<table>
<thead>
<tr>
<th>Period</th>
<th>1% Critical Value</th>
<th>5% Critical Value</th>
<th>10% Critical Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Period 1 - No Trend</td>
<td>-3.482</td>
<td>-2.884</td>
<td>-2.574</td>
</tr>
<tr>
<td>Period 1 - Trend</td>
<td>-4.012</td>
<td>-3.439</td>
<td>-3.139</td>
</tr>
<tr>
<td>Period 1a - No Trend</td>
<td>-3.508</td>
<td>-2.89</td>
<td>-2.58</td>
</tr>
<tr>
<td>Period 1a - Trend</td>
<td>-4.038</td>
<td>-3.449</td>
<td>-3.149</td>
</tr>
<tr>
<td>Period 1b - No Trend</td>
<td>-3.541</td>
<td>-2.908</td>
<td>-2.589</td>
</tr>
<tr>
<td>Period 1b - Trend</td>
<td>-4.088</td>
<td>-3.472</td>
<td>-3.163</td>
</tr>
</tbody>
</table>

35
6. Results

6.2 Short-Run and Long-Run Relationships

To conclude if a long-run and/or short-run relationship exist between the given macroeconomic indicators and S&P500 the ARDL model is utilized. The results for each time period can be seen in Table 8, the corresponding diagnostic tests in Table 9 and Figure 8-13. To conclude if the indicators have different interrelations depending on the time period of choice, the ARDL model is performed on the entire sample and two sub-samples as in the previous Section 6.1. Note that the data sample is divided into three time periods and with three data samples there are different problems that needs to be assessed in each sub-sample. The alternations of the model including a discussion of the results will be given below. Furthermore note that the measurement of importance is defined by the existence of a relationship between the variables rather than the coefficient magnitude or the p-value (see Section 5.7 and Section 7.2.1 for a further discussion about this topic). Insignificant variables implying that we cannot reject that the coefficients are zero will not be discussed in detail, unless there are some extreme cases.

6.2.1 Results from the ARDL Model

The final results from the ARDL model can be seen in Table 8. However to produce satisfactory results a few adjustments had to be made. Also, we do not discuss the lagged dependent variables (they can be included to increase the fit of the model), even though they might display significant coefficients in the results as it is misleading that historical values has predictive power in current value of the dependent variable. The effect on S&P500 should rather be captured in the other economic indicators, i.e. the independent variables.

For each sub-sample period a few adjustments had to be made. In contrast to the entire period analysis between 2000-2016, period 1a shows signs of instability in the coefficients from the CUSUMSQ test during the recession period 04/2001-11/2001 defined by The National Bureau of Economic Research (NBER) recession indicator and after the fall of Lehman Brothers in October 2008. The existence of instability during 2001 for a small sample size is not unexpected as there were a few events during this year that may have had an impact on the performance of the market such as the 9/11 terrorist attack, Enron bankruptcy and the invasion of Afghanistan. To counteract the instability we reduce the sample by removing the five end observations that covers the Lehman brothers bankruptcy. Furthermore there are a few remedies for the 2001 instability. As seen in Table 8 and Figure 8-9 by increasing the sample size events of this kind are often diluted, standard errors are decreased and the problem become less evident. As the sample size cannot be increased any further we are left with the inclusion of a stabilizing dummy variable (\[D_R\]) for the period 04/2001-03/2002 following NBER (2016) recession and the aforementioned events. The dummy variable was included in the pre-analysis for 2000-2016 but showed no significance (and was therefore removed) which supports the conclusion that it is a sample size related instability.

Furthermore, during time period 1b the pre-analysis of the variables propose a shift in the relationship between the initial jobless claims (IJC) and the money supply (M1) which can be seen in Table 16 in Appendix A.3. This was only evident
for these variables in this time period. There are several reasons why this relation suddenly appears e.g. Quantitative Easing, an indirect relationship or simply due to the small sample size. The indirect relationship may be created e.g. by the low interest rates which boosts the economy by increased lending (increased money supply) which lowers the unemployment level and thus the unemployment benefits.

By analyzing the entire sample size (2000-2016) there is no evident relationship between IJC and M1, which support the fact that the relationship is most likely a consequence of a decreased sample size or an extreme market event after 2009. As the time period is fixed between 2009 up to the current date, it is not possible to change the sample size in order to adjust for the relationship in the OLS regression. Therefore in accordance with Brooks (2014) two models (ARDL) are made, one for which IJC is included, and one for which M1 is not and vice versa. When the IJC is included and M1 excluded the model fails the F-bounds test so the results are rendered useless. However when M1 is included and IJC excluded the model completes the F-bounds test.

A possible explanation for the lack of a long-run relationship between the indicators when money supply is excluded is that money supply is closely connected to economic activity and interest rates. As the interest rates have been low throughout this period due to e.g. Quantitative Easing raising capital has been fairly cheap inducing increased lending (money supply increase) for e.g. building projects (building permits) and a general expansion in the economy (increased optimism, spending, production) (Joyce et al. 2012) i.e. money supply has an indirect relationship with many of the indicators. Thus we can conclude that the money supply is an important factor in this time period which moves together with the contemplated indicators and S&P500.

The results of the ARDL model can be seen in Table 8 where the upper bracket presents the long-run coefficients and the lower bracket corresponds to the short-run coefficients. The values in the parenthesis is the standard error and the coefficient is outside the parenthesis. The symbols *, **, *** represents a significance level of 5%, 2.5% and 1% respectively. SIC is the optimal lag with alteration depending on potential biases. From a mathematical perspective the interpretation of the coefficients in Table 8 is of a percentage nature as the data is log-transformed e.g. the long-run coefficient for ISM is 0.176 which implies that when ISM increase by 1%, S&P500 has increased on average by 0.176 %. The same interpretation applies for the other coefficients.

The F-bound test is passed for all the models except for period 1b where the F-bound test is inconclusive on 2.5% level. See Table 9 for the F-bound statistic and the critical values. To assure the existence of a long-run relationship in accordance with Section 5.6.2 we utilize the t-statistic which is −4.259 and given the following critical values: (−2.86,−4.19),(−3.13,−4.46),(−3.43,−4.79) (Pesaran et al. 2001) we can conclude that a long-run relationship exist. The error correction term is also negative and significant for all the models which further supports the long-run relationship and that the variables converge to a long-run equilibrium after a distortion in the indicators.
6. Results

Table 8: Final ARDL results. ***,*** represents a significance level of 5%, 2.5% and 1% respectively. Standard error in parentheses. The results are further divided based on long-run and short-run results.

<table>
<thead>
<tr>
<th>Covariate/Regressand</th>
<th>Period 1</th>
<th>Period 1a</th>
<th>Period 1b</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(ISM)</td>
<td>0.176</td>
<td>-0.042</td>
<td>0.627***</td>
</tr>
<tr>
<td></td>
<td>(0.321)</td>
<td>(0.404)</td>
<td>(0.222)</td>
</tr>
<tr>
<td>ln(IJC)</td>
<td>-1.16***</td>
<td>-1.05***</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>(0.194)</td>
<td>(0.216)</td>
<td>-</td>
</tr>
<tr>
<td>ln(BP)</td>
<td>-0.270***</td>
<td>-0.225</td>
<td>0.031</td>
</tr>
<tr>
<td></td>
<td>(0.086)</td>
<td>(0.158)</td>
<td>(0.144)</td>
</tr>
<tr>
<td>PS</td>
<td>0.180*</td>
<td>0.310**</td>
<td>0.037</td>
</tr>
<tr>
<td></td>
<td>(0.09)</td>
<td>(0.132)</td>
<td>(0.054)</td>
</tr>
<tr>
<td>ln(MC)</td>
<td>0.3</td>
<td>0.379*</td>
<td>0.455***</td>
</tr>
<tr>
<td></td>
<td>(0.219)</td>
<td>(0.323)</td>
<td>(0.150)</td>
</tr>
<tr>
<td>ln(M1)</td>
<td>0.388***</td>
<td>0.896*</td>
<td>0.909***</td>
</tr>
<tr>
<td></td>
<td>(0.106)</td>
<td>(0.425)</td>
<td>(0.164)</td>
</tr>
<tr>
<td>Δln(ISM)_t</td>
<td>0.224*</td>
<td>0.125</td>
<td>0.278</td>
</tr>
<tr>
<td></td>
<td>(0.108)</td>
<td>(0.129)</td>
<td>(0.174)</td>
</tr>
<tr>
<td>Δln(ISM)_{t-1}</td>
<td>0.235**</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>(0.097)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Δln(ISM)_{t-2}</td>
<td>0.181*</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>(0.091)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Δln(IJC)_t</td>
<td>-0.204***</td>
<td>-0.212***</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>(0.058)</td>
<td>(0.0678)</td>
<td>-</td>
</tr>
<tr>
<td>Δln(BP)_t</td>
<td>0.00836</td>
<td>-0.197*</td>
<td>0.203*</td>
</tr>
<tr>
<td></td>
<td>(0.066)</td>
<td>(0.093)</td>
<td>(0.092)</td>
</tr>
<tr>
<td>Δln(BP)_{t-1}</td>
<td>-0.178</td>
<td>0.127</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.099)</td>
<td>(0.088)</td>
<td></td>
</tr>
<tr>
<td>ΔPS_t</td>
<td>0.0136</td>
<td>0.028***</td>
<td>0.007</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.009)</td>
<td>(0.016)</td>
</tr>
<tr>
<td>Δln(MC)_t</td>
<td>0.212***</td>
<td>0.119</td>
<td>0.086</td>
</tr>
<tr>
<td></td>
<td>(0.061)</td>
<td>(0.074)</td>
<td>(0.092)</td>
</tr>
<tr>
<td>Δln(M1)_t</td>
<td>-0.141</td>
<td>-0.318</td>
<td>0.704</td>
</tr>
<tr>
<td></td>
<td>(0.253)</td>
<td>(0.338)</td>
<td>(0.375)</td>
</tr>
<tr>
<td>Δln(SP500)_{t-1}</td>
<td>-0.129</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>(0.079)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Δln(SP500)_{t-2}</td>
<td>-0.276***</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>(0.076)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>ΔECM_{t-1}</td>
<td>-0.169***</td>
<td>-0.187***</td>
<td>-0.453***</td>
</tr>
<tr>
<td></td>
<td>(0.038)</td>
<td>(0.0584)</td>
<td>(0.106)</td>
</tr>
<tr>
<td>D_{ISM&gt;50}</td>
<td>-0.027**</td>
<td>-0.031**</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.013)</td>
<td>(0.024)</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.524</td>
<td>-2.172</td>
<td>-10.549***</td>
</tr>
<tr>
<td></td>
<td>(0.843)</td>
<td>(2.286)</td>
<td>(3.310)</td>
</tr>
<tr>
<td>DR</td>
<td>0.196**</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>(0.0823)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>ΔDR</td>
<td>0.104***</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>(0.0283)</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>
As mentioned in Section 5.8 the ARDL model in similarity to OLS estimation tries to find the best linear unbiased estimator (BLUE) and therefore diagnostic tests need to be conducted. As seen in Table 9 the results are not biased by serial correlation (See also additional test in Appendix B.4), heteroskedasticity, misspecification (wrong functional form) or non-normality on a 10% level. Furthermore the standard errors and the confidence intervals are small i.e. they are on an acceptable level which indicates no problematic collinearity for any variables. See Appendix A for p-values and more. The test for stability is quite extensive and is therefore shown in Section 6.2.2. However as indicated in Section 6.2.2 the ARDL model shows no sign of instability.

Table 9: Diagnostic tests and F-bound test statistics for the main ARDL models. The p-value is in the parenthesis, and the test-statistic outside parenthesis. Source: Authors computations, Pesaran et al. (2001)

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Period 1</th>
<th>Period 1a</th>
<th>Period 1b</th>
</tr>
</thead>
<tbody>
<tr>
<td>F-Bound statistic</td>
<td>4.749</td>
<td>4.760</td>
<td>3.112</td>
</tr>
<tr>
<td>$R^2$</td>
<td>32.84%</td>
<td>39.5%</td>
<td>31.52%</td>
</tr>
<tr>
<td>Serial Correlation</td>
<td>0.17 (0.680)</td>
<td>1.65 (0.199)</td>
<td>1.061 (0.303)</td>
</tr>
<tr>
<td>Heteroskedasticity</td>
<td>187.0 (0.466)</td>
<td>103 (0.454)</td>
<td>78.00 (0.447)</td>
</tr>
<tr>
<td>Functional Form</td>
<td>2.17 (0.117)</td>
<td>0.45 (0.640)</td>
<td>0.47 (0.626)</td>
</tr>
<tr>
<td>Normality</td>
<td>3.75 (0.154)</td>
<td>1.25 (0.536)</td>
<td>1.328 (0.515)</td>
</tr>
</tbody>
</table>

F-bound test Critical Values

<table>
<thead>
<tr>
<th>F-bounds test</th>
<th>5%</th>
<th>2.5%</th>
<th>1%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Critical values period 1</td>
<td>[2.32 , 3.50]</td>
<td>[2.60 , 3.84]</td>
<td>[2.96 , 4.26]</td>
</tr>
<tr>
<td>Critical values period 1a</td>
<td>[2.45 , 3.61]</td>
<td>[2.75 , 3.99]</td>
<td>[3.15 , 4.43]</td>
</tr>
<tr>
<td>Critical values period 1b</td>
<td>[2.62 , 3.79]</td>
<td>[2.96 , 4.18]</td>
<td>[3.94 , 4.68]</td>
</tr>
</tbody>
</table>

The results are seemingly unbiased but before we begin with the analysis, we want to clarify one result and one interpretation aspect. Firstly, as previously mentioned the long-run coefficients are in level ($y$) while the short-run coefficients are in first difference ($\Delta y$). All macroeconomic indicators in Table 8 provide explainable insignificant coefficient signs except for ISM manufacturing for period 1a where the coefficient is surprisingly negative, albeit insignificant and small in magnitude. As we cannot reject the hypothesis that the coefficient is zero i.e. the coefficient is insignificant, the contribution of the parameter is not evident. By doing a one-sided t-test with the calculated t-statistic $H_0 : \ln(\text{ISM}) \geq 0$, p-value = $0.404/2 = 0.202$ we cannot reject the hypothesis that ISM has a positive or zero impact on S&P500. Thus we do not consider the sign as a problem.

Secondly, the macroeconomic variable that provide the largest impact in terms of the coefficient magnitude are the IJC indicator such that when IJC has increased by 1%, S&P500 has decreased by 1.16% in the long-run. However, there are some practical issues with the interpretation of the coefficients. The magnitude does not necessarily provide any information about which factor that has the strongest relationship with S&P500 as a 1% increase in one variable cannot necessarily be compared with a 1% increase in another. There are other data transformations that could have provided another interpretation of the results but the problem of the interpretation will still remain. The impact and appropriateness of these transformations are further discussed in Section 7.2.1.
6.2.2 CUSUM and CUSUMSQ Tests

As seen in Figure 8-13 the CUSUM or CUSUMSQ line (See Section 5.8.1) do not break the limits which imply that the coefficients are stable. Given the completed diagnostic tests we can begin with the analysis.
6.2.3 Predicted Versus Actual Values on S&P500

The mathematical approach in this thesis is inference rather than prediction but to illustrate the estimates the predictors for each time period model are plotted against the actual values. The predictors are the predicted values of S&P500 from our ARDL model. One of the most important characteristics to consider between the actual values and the predicted values is if the values are severely different and if there are large spikes in the predictors. Characteristics of this kind can imply that the coefficient estimates are poorly produced. Larger versions of Figure 14, Figure 16 and Figure 18 can be seen in the Appendix B.3.

Figure 14-19 represent the in-sample prediction values from the ARDL model versus the actual values for S&P500. Figure 14-15 represents the entire sample period, and as seen in the figures the predicted values follow the actual values during the entire period. For a few data points the model overestimates or underestimates the actual values but there are no severe deviations or large spikes. The scatter plot reveals that the estimates and consequently the coefficients are satisfactory as the actual values and the predicted values form a linear relationship i.e. when if the actual values are large the predicted values also tend to be large and vice versa.

The in-sample predictors for period 1a can be seen in Figure 16-17. Figure 16 shows that our model also makes reasonable predictions versus the actual index. The deviation from the actual values are seemingly larger than for Figure 14 however this could be due to a smaller data sample which makes the variance higher and therefore the model erroneously over- and underestimate the predicted values. It does not capture the full magnitude of the peaks in the years leading up to the financial crisis. However, following the Dotcom bubble, the model makes predictions that are reasonably in-line with the actual outcome of the S&P500. The interpretation is the same for the scatter plot Figure 17. Furthermore, in accordance with the entire sample period estimates, the scatter plot reveals a linear trend between the actual values and the predicted values.
Finally for period 1b, our third ARDL-model predicts higher value for the S&P500 for a number of years, following the European debt crisis. The explanation probably lies in the fact that Money supply (M1) has become more volatile and that the sample has been reduced. The scatter plot reveal once again a linear relationship between the actual values and the predicted values.

The predictors tend to over-estimate and under-estimate evenly for all time periods which is illustrated in Table 10. As seen in Table 10 the Period 1 predictors over-estimate the actual values 52% of the time and under-estimate 48% of the time. The interpretation is the same in the other time periods and accordingly the estimates have a good spread.

In general the predictors seem to follow the actual values but as they are in-sample predictors they can suffer from over-fitting. Thus, to illustrate the strength of the model and our choice of variables further we calculate the pseudo out-of-sample predictors as well. For those unfamiliar with the term out-of-sample, we provide an brief explanation below.
The out-of-sample model is updated on a monthly basis and in order to have a sufficient amount of data for reliable estimates we start the model at the 50th data point (around 2006). This implies that the ARDL model estimate S&P500 based on the indicator data up until the 50th data point, constructs a forecast of S&P500 for the next month (data point 51) by using the calculated coefficient estimates and the actual values of the explanatory variables. The model is then re-estimated based upon data including 51st data point and a forecast for the 52nd data point is constructed and so on. This is done, until the we have used the entire sample. The lag for each indicator is set to one, in order to make sure that for each step, an additional observation is added to the calculation. Note that if the optimal lag (based on SIC) is chosen, the number of observations can decrease (increase) for each step as the lag order can increase (decrease).

The results of the out-of-sample regressions can be seen in Figure 20-21. The predicted values still follow the actual values in a satisfactory manner and the scatter plots reveal a linear relationship. This indicates that the chosen indicators have some relationship with S&P500. However, to conclude if the model is possible to use in practice further research has to be done which is outside the scope of this thesis.
7 Analysis and Discussion of Findings

The purpose of this thesis is to investigate if and how certain macroeconomic indicators may have a relationship with the US stock market development in the short- and the long-run. Therefore, in this section we intend to answer our research questions on the basis of the results in Section 6.2:

RQ 1.1 What are the short and long-run relationships between our chosen set of macroeconomic indicators and the US stock market?

RQ 1.2 Do the set of macroeconomic indicators have different relationships with the stock market during different time periods?

RQ 1.3 Which and when are the macroeconomic indicators most important for describing the stock market development?

This section is divided into two major parts. First the results are explained from a macroeconomic perspective to analyze the economic significance of the coefficients. This includes a comparison between our results and previous research. Finally, we will have a discussion about the model setup in terms of how to measure importance and the quality of scientific work.

7.1 Macroeconomic Interpretation

In this section we discuss whether the results are logically plausible by proposing macroeconomic explanations for the results given in Section 6.2. The analysis cover, both if relevant the indicators characteristics in terms of how they are measured and how they are related to different macroeconomic interrelationships. As reminder note that period 1, period 1a and period 1b correspond to the data sample around 2000-2016, 2000-2009, 2009-2016 respectively. The analysis is quite extensive and for the well-read reader within the field of macroeconomics a brief summary of the analysis is given below. The analysis will be described in more detailed thereafter (see Section 7.1.1-7.1.6).

- **Initial Jobless Claims:** For the indicator initial jobless claims, the coefficient was significant and negative in the long-run as well as in short-run for all relevant models. As the indicator measure the number of people applying for unemployment insurance an increase should imply a decrease in the overall wealth of the population. The future loss of income for these people will have an impact on the consumer confidence, consumer spending and consequently business investments which leads to lower corporate profits.

- **Building Permits:** An increase in the indicator building permits should have a positive effect on S&P500 as more houses are to be built and consequently the sales for industries with a relation to housing should increase through the multiplier effect. However, our results show that building permits have a negative relation to the stock market both in the long-run and short-run for some time periods. A plausible explanation of the results is that there have been time periods where the stock market and the housing market
Analysis and Discussion of Findings

Haq, Larsson have moved in opposite directions which indicate that building permits may reflect investors belief of the future house market development rather than the economic development. In a regular stock market environment, with no extreme market bubbles (speculation), building permits seems to follow the theoretical positive relationship in the short-run (Table 8, Period 1b).

- **M1 Money Supply:** The money supply always has a positive long-term relationship with the S&P500 which is supported by macroeconomic theory as an increase in the money supply can increase investments and spending.

- **Michigan Consumer Sentiment Index:** The relation both in the long-run and short-run are positive which is supported by macroeconomic theory as a higher consumer confidence should results in a higher consumer spending, raising corporate profits and subsequently have a positive effect on S&P500. However the significance alters between the periods which may be due to the impact of turning points in the economy and events.

- **Personal Spending:** Our results show a positive relationship both in the long-run and short-run between S&P500 and personal spending which was expected. Personal spending has a significant long-run relationship for period 1 and period 1a. For period 1b the long-run coefficient was not significant, where a possible explanation might be in the rise of personal savings rate after the financial crisis.

- **ISM Manufacturing:** For period 1, the long-run relationship was positive, but not significant which is explained by that ISM Manufacturing was not able to capture deviations in the stock market due to underlying characteristics. Thus when the market is not in a clear bear and bull state one should be careful when interpreting the indicator from a long-run perspective instead the short-run interpretation is preferred. For period 1b, the long-run coefficient is positive and significant which supports the theory that if the economy is moving out from a recession according to ISM, one may expect a increase in the stock market in the long-run.

### 7.1.1 Initial Jobless Claims

From a mathematical perspective initial jobless claims (IJC) seems to have a significant negative long-run and short-run relationship with S&P500 for all relevant models. The indicator is therefore important to consider if one wants to analyze stock market movements given any time frame. To illustrate the relationship consider Figure 22, where the inverted IJC (1/IJC) is compared to S&P500. As seen in the Figure 22, IJC and S&P500 do follow each other and have done so for a long time.

The negative sign was expected and is similar to the results provided by Sirucek et al. (2012) who propose that unemployment is one of the most significant determinants of S&P500. Given IJC’s strong negative relationship with S&P500
one may wonder why this relationship exists. First consider that IJC is based on actual reports from state agencies in the US and is issued on a weekly basis. Thus an increase in IJC provides a reliable indication that more people apply for unemployment insurance i.e. more people are losing their jobs every week. The loss of future prospects and income for these individuals will eventually reduce overall consumer confidence, consumer spending and consequently businesses will have to cut-back on their investments. Therefore if IJC increase it is an indication of an economy in a downturn, and by the same means, if the number of claims decline substantially, the economy is on the uprise. Historically, this indicator has been able to tell when the economy is reaching a turning point. An example of this is when first-time claims reaches its peak, the economy reaches its bottom two to three months after, before beginning its recovery phase. The publication frequency in combination with that IJC measure the number of people that apply for claims (unemployment insurance) therefore render the indicator extremely important and is considered to reflect the current and future state of the economy (Baumohl 2012).

Beyond IJC’s relationship with economic activity described above it may impact the stock market by other more far-reaching relationships. The equity market will according to economic theory be affected positively by an increasing number of initial jobless claims as it diminishes the inflationary pressure and thereby decrease the interest rate. However, if the interest rate falls, the USD will not be as attractive to hold, more so if bond yields or other interest-bearing investment opportunities are higher in other countries. Therefore, an increasing number of jobless claims might turn away investors from the US equity markets. The USD will be weakened by this in currency exchange markets. This can provide support to exporting companies as their operating expenses are in USD and revenues in foreign currencies which in turn can provide support for parts of the US equity markets due to higher corporate profits.

The overall implication for investors is to closely evaluate IJC and analyze how the market may develop. Due to the characteristics of the indicator and as the data is presented on a weekly basis, it is still erratic to use it for analysis for only one week as holidays during a week, or a four-day workweek can dramatically distort data. More advisable is to use a moving average of 4 weeks or as we have proceeded...
by using the results for the last datapoint for every month. By using a moving average the volatility of the weekly claims is smoothed out, however information might be lost in the process of doing so and it is therefore advisable to use actual data points as done in this thesis.

7.1.2 Building Permits

Building permits is of importance to any serious financial institution or investor that would like to know whether the economy is moving into a recession or an expansionary economic state. A good example of why it plays a major role is that there has never been a recession in the US economy when the housing sector continued to stay strong, except when the IT bubble of 2001 burst. The recession of 2001 was still very short-lived and not very deep. When an economy is nearing the breaking point of a recession the residential real estate sector is one of the first sectors to shut down and vice versa, when the economy moves into an expansionary phase the first lead can be seen in the same sector (Baumohl 2012).

The reason for why the housing sector and more specifically building permits are ahead of the economy as an economic indicator is because of its sensitivity to interest rates. An expansionary economy that is reaching overheating pushes interest rates higher. This allows for higher mortgage rates, which lowers the demand for residences and thereby depresses future construction. Constructors are also less likely to apply for loans when rates are higher. In the same way, when interest rates are low and home prices are declining, which is typically the case in a weak economy, the demand for homes are reawakened, due to the lower price. Construction companies also tend to borrow more before the interest rates increase again (Baumohl 2012).

Building permits also affect the economy through so called multiplier effects which is when the pace of housing construction changes other industries experience a positive effect. If we consider who benefits when housing is strong, we can see that a jump in residential construction drives up the demand for inter alia steel, electricity, wood, glass, plastic, wiring, concrete and piping. An increased demand for residential construction also increases the need for skilled workers such as electricians, carpenters and bricklayers (Koller et al. 2015). So even though the business for constructing real estates accounts for 5% of GDP, the expected total effect is substantially larger.

Given the aforementioned description of building permits the resulting significant negative signs for period 1 and period 1a from the ARDL models are surprising. There are a few possible reasons why both some short-run and long-run coefficients are negative. To understand the sign we have to separate the theoretical relationship with the relationship given by the data. First consider that during 2000s there have been time periods when the stock market have continued to increase (decrease) while building permits has decreased (increased). The most evident time periods are the dot-com aftermath and the equity bubble between 2001-2003, the house bubble around 2002-2006 two years before the financial crisis and the slow recovery of the housing sector between 2009 to mid-2011. See Figure
The negative coefficient sign imply that the negative events in the data outweigh the proposed positive theoretical relationship. This provides a slight indication that the housing sector possibly have a relationship with the economy but there may also be time periods when it is separated from the stock market. A supportive argument is that a building permit is a permit that must be filed before the shovel hits the ground i.e. before the construction of a new or existing building can legally occur (Baumohl 2012). Thus it might be sensitive to future market prospects and may therefore not necessarily reflect the state of the economy rather it may reflect how investors believe the housing market will develop. When the equity and housing bubble are removed (period 1b) the signs turns positive yet insignificant in the long-run which justify the suggested explanation above. In a regular environment with no extreme market bubbles, building permits therefore seems to follow the theoretical relationship at least in the short-run.

To summarize, investors in the US equity markets should be alarmed if there is a prolonged weakness in housing, however when the housing activity is vibrant and the inflation targets are being met, shareholders may typically view the indicator as positive as from previous inference a strong housing activity can be beneficial for other companies than residential construction. However investors may carefully interpret the indicator and should evaluate if the increase in building permits is an indication of an expanding economy or due to certain house market dynamics.

7.1.3 M1 Money Supply

From a mathematical and macro economical perspective money supply seems to have a long-run relationship with S&P500. In all time periods the long-run coefficient for money supply is positive and significant. The results are both similar and dissimilar to the research by Humpe & Macmillan (2009) and Flannery & Protopapadakis (2002). As shown in Sellin (2001) this is unsurprising as many different researchers have proposed different conclusions regarding M1s relationship with equity prices. The different conclusions can be a result of that the money
supply may have different impacts on the stock market given the different time periods under which the research were conducted. Humpe & Macmillan (2009) found a positive but an insignificant coefficient for money supply between the period 1965-2005. As our results show that there is a significant relationship one may wonder why the results are different. An explanation could be that there have been for example a shift in the money supply relationship before 2000 which may be due to different events or market mechanisms during the beginning of the 21th century. A recent shift in the money supply would have a lesser impact for Humpe & Macmillan (2009) as the shift could be diluted in their data sample as they are investigating a very long time period. Flannery & Protopapadakis (2002) used a smaller data sample (1980-1996) and utilized a GARCH model to conclude that unlike 17 other macro series announcements the money supply indicator M1 affect both the level and the conditional volatility of stock returns on the US stock market. Comparing the results the money supply therefore seems to have become more vital for the stock market development in recent years.

In order to assess the money supply impact on the stock market, we look at the macroeconomic fundamentals. The money supply can impact the stock market by at least three different market mechanisms:

1. Real activity hypothesis: Money supply changes will alter the expectations of future output (Sellin 2001) i.e. money supply variations may impact stock prices by its positive relationship with economic activity through its connection to interest rates. For example an increasing money supply may put a downward pressure on the interest rates which boosts interest-sensitive spending such as investments.

2. The Keynesian hypothesis: Money supply can have a negative impact on stock prices by its relationship to unanticipated and future inflation. Keynesian theory states that when the money supply changes it will affect asset prices if it alters the expectations of future monetary policy. If for example, the money supply increase, market participants will anticipate a contractionary monetary policy in the future which will lead to e.g. less investments and consequently increased interest rates. Thus lowering stock market prices by a higher discount rate and lower expectations regarding future cash flows due to decreased economic activity. (Sellin 2001)

3. An increase in the money supply by e.g. Quantitative Easing (QE) can reduce interest rates inducing a shift from interest bearing assets to non-interest bearing assets such as equities and consequently lead to an increase in stock market prices.

As mentioned above the money supplys connection to the stock market is often through an indirect relationship with the interest rates as the intermediate factor. The role of the money supply in terms of interest rates can easily be explained by the liquidity preference model of the interest rate (Krugman & Wells 2013) shown in Figure 24. The quantity of money supplied by the FED (money supply curve) can be altered by e.g. open-market operations and changes of the reserve requirement. The money demand curve can shift by among other things changes the
aggregate price level (inflation) and changes in real GDP. The equilibrium where the demand is equal to the supply establish the interest rate. As seen in Figure 24 a decrease of the quantity of money reduce the interest rate.

Figure 24: Liquidity Preference Model of the Interest Rate. Source: Krugman & Wells (2013)

Nevertheless given these three mechanisms it seems that they have offset each other in the past or the money supply has not increased fast enough in order for mechanism one and three to get an actual impact on the stock market. This would explain why money supply have not been a significant indicator for the stock market in the past. This raises the question if the fundamentals behind money supply has changed as our results indicate a significant long-run relationship with the stock market.

Figure 25-26 depicts the Monetary Supply indicator M1 which includes the most liquid money components of money supply such as physical money and checking accounts. As seen in Figure 25 the money supply increased by around 500 billion USD 1982-2000 (18 years) which is about the same increase as between 2000-2008 (only 8 years) and about a third of the increase after the financial crisis i.e. M1 is growing faster and faster. After the financial crisis in 2008 M1 started increasing rapidly from having approximately 800 billion USD in treasury notes. Following the crash of the investment bank Lehman Brothers, the Federal Reserve started buying mortgage-backed securities for 600 billion USD in response to a weak economy and high unemployment (Krugman & Wells 2013). In the first quarter of 2009, the Fed had doubled their balance sheet, but continued with further asset purchases during the following years. In November 2010 FED started buying 600 Billion in Bonds and they continued to buy mortgage-backed securities in September 2012. The consequence of the open market operations (Quantitative Easing) are quite evident as the federal funds rate (interest rate) decreased sharply from being around 1.5%-6% during 2000-2009 to be around 0.0%-0.25% for the following years (OECD 2016A). Thus making the aforementioned mechanisms, especially point one and three of the money supply relevant for explaining the calculated positive and significant relationship which Humpe & Macmillan (2009) didn’t capture in their sample (1965-2005).

Given the increase in S&P500 after 2009 one may propose that given our and Humpe & Macmillan (2009) results, aggressive monetary policy and Quantitative
Easing (QE) seems to have a positive effect on the stock market. As stated in Joyce et al. (2012) the consensus of the literature regarding QE is that the unconventional monetary policy does work in terms of boosting the economy. However, the economic recovery remains fragile and whether the relationship between money supply and S&P500 is a consequence of QE or not continues to be unknown and is outside the scope of this thesis.

Looking at the short-run components, the short-run relationship with S&P500 is not evident which may be due to the fact that monetary changes are time-consuming i.e. it takes time for the effect of a monetary policy to take place. Thus delaying any stock market reaction.

To summarize, what we can conclude is that given our data sample money supply has a positive and in general a significant relationship with the stock market in the long-run due to its connection to economic activity. The relationship has become stronger after the financial crisis which might be an effect of an aggressive monetary policy in terms of QE and consequently very low interest rates. In the current state of the economy with a relative fast increase in the money supply, M1 therefore seems to be an important indicator for describing the stock market development. However, if that relationship will continue to exist when the aggressive monetary policy ends is unforeseen.

### 7.1.4 Michigan Consumer Sentiment Index

Consumer expenditure account for over half of the economy’s total demand in the United States. The happiness of the consumers is important as when consumers feel less confident of the economy they tend not to be willing to make major purchases such as houses and cars which may derail the economic activity (Baumohl 2012). Falling confidence is therefore not favorable towards equities as it is an indication of declining business sales and therefore one may assume that the Michigan consumer sentiment index should be in a positive relationship with S&P500. As seen in Table 8 the coefficients both in the long-run and short-run are positive but the significance alter depending on the time period. Looking at the primary results i.e. between 2000-2016 the change in the indicator is significant while the long-run relationship is insignificant and vice versa for the other time periods. The significance of the variables can be affected by many factors including the lag structure, sample size and the interrelationship between the independent variables. To de-
determine the cause of the results we delve deeper into the Michigan consumer index.

The Michigan consumer index is statistically calculated on a monthly basis by estimating consumer attitudes of 500 adults on financial and income situations by using a survey (Baumohl 2012). Thus the indicator is just like similar indicators e.g. the Conference Board Consumer confidence index, based on the emotional sentiment of the population. The emotional aspect of sentiment indicators induce uncertainty when analyzing them, as a single negative news report could swing the mood of the population and consequently how respondents answer the survey. For example, for the Michigan Consumer Index, which is depicted in Figure 27, we can see that the index dropped substantially during the financial crisis of 2008. This in turn makes company sales lower when the economy experiences the contraction period. After the financial crisis, we can see that there has been an upgoing trend with exception of the European debt crisis in 2011.

Figure 27: S&P500 and Michigan Consumer. Source: Authors computations, Bloomberg, Macrobond

For a large sample the emotional effect of news and events e.g. terrorist attacks may be diluted as the sample may contain a similar amount of negative and positive news/events as well as time periods when the emotional effect is not that evident. However for smaller samples news reports and the general nature of the market becomes more evident. The switch in significance is therefore fairly intuitively as emotional swings due to bear and bull markets are diluted in larger samples but when the sample is divided into two sup-samples the long-run relationship becomes more evident due to the current market dynamics. For example after 9/11 both S&P500 and consumer confidence fell, hence events of this kind makes the variables follow each other quite well if one analyze occasional periods (see Figure 27). In general for a larger sample i.e. 2000-2016 the level relationship is therefore not that apparent rather the fluctuations from the long-run equilibrium (short-run effects) becomes more important. The results after the financial crisis also indicates that the indicator can be used to detect a turning point in the economy as the long-run coefficient become large for this period. This conclusion is similar to the one proposed by Baumohl (2012) i.e. the market sensitivity to optimism indices are at a medium level but can be high at turning points in the economy. Hence while analyzing the indicator it is of importance to consider if there has been a turning point in the economy, then the indicator might pro-
provide an indication of a future long-run decrease/increase of the stock market i.e. whether the increase/decrease will continue. But overall the short-run relationship is significant.

### 7.1.5 Personal Spending

The positive coefficients for personal spending both in the long-run and short-run throughout all models was expected. Expenditure from consumer or personal spending rule the economy as it is the main driving force of inter alia sales, imports, factory output, investments and growth in jobs. Consumers spend when they have a reliable cash flow stream of income. Personal spending will continue to rise as long as personal income does. Personal income which is not analysed in this context accounts for the money that a household receives pre-tax, and what is really measured and of interest in this case is the disposable income, which is the amount of money consumers have left after taxes and non-tax payments.

Historically, the average household have spent approximately 95% of their total income which has accounted for roughly 2/3 of GDP and therefore theoretically should have a strong impact on the equity markets through higher corporate profits (Koller et al. 2015, Baumohl 2012). There are three broad categories that consumers are spending their money on, namely, durable goods, non-durable goods and services. Durable goods are products that are meant to last more than three years and thus include cars, refrigerators, washing machines etc. as this category is the most expensive it accounts for the smallest share of personal spending at roughly 12-14%. Non-durable goods account for 30% of the total spending and include commodities such as food and clothing. Lastly, services, which is the fastest growing constituent of personal spending has grown from accounting 40% of personal spending to 60% currently and make up medical treatment, legal fees, cinema, travelling etc.

In our model for the period 1 and period 1a, personal spending has a significant long-run relationship on the 5 percent and 2.5 percent significance level. This is expected because an increase in disposable income will result in an increased spending. If the spending rate does not increase, the savings rate increase. However, looking at the history of personal savings rate, the trend was declining between 1980 to 2005 as viewed in Figure 28.

The coefficient for personal spending in the time series model for the period after the financial crisis is smaller compared to other periods and insignificant on long term. An explanation for this is that the financial regime changed substantially after the financial crises, as the economy moved out of the recession and into an expansion. Another possibility for the lack of a significant long-run coefficient in the second period is the increase in the disposable income without a corresponding increase in personal spending. This is a plausible explanation of consumer behavior following a financial crisis.
In terms of industrial production the results seem to contradict previous research (Humpe & Macmillan 2009, Chaudhuri & Smiles 2004, Nasseh & Strauss 2000) as the long-run coefficient is insignificant except for the period 1b. Furthermore a surprising result is the negative sign of ISM manufacturing during period 1a however it is insignificant and small in magnitude. As a reminder we restate previous statements in Section 6.2: The contribution of the parameter is therefore not evident as we cannot reject the hypothesis that the coefficient is zero. By doing a one-sided t-test with the calculated t-statistic $H_0: \ln(\text{ISM}) \geq 0$, p-value $= 0.404/2 = 0.202$ we cannot reject the hypothesis that ISM has no or a positive impact on S&P500. Thus we do not consider this as a problem.

For the entire sample period the long-run coefficient is positive and insignificant. A logical explanation to the insignificant coefficient is that ISM manufacturing is unable to capture all deviations in the stock market returns due to its underlying characteristics. In terms of production indices and especially ISM the magnitude of the indicator may not always be as important as the trend or the momentum of the production. Consider the following analogy: if ISM increases from 37 to 41 during a recession it may be considered bad as the indicator is still under 50 and the economy is very weak. Hence in the short-run the stock market rise as the production have increased but in the long-run the stock market either decrease or remain still as we are still in a recession. However, if ISM has been increasing for consequential months from 30 to 41 the reaction might be positive both in the long-run and short-run as it is a signal for economic recovery. Furthermore if the index goes up when business activity is already high e.g. from 59 to 62, stock prices could fall in the long-run as investors might believe that the economy is in danger of overheating (Baumohl 2012). Thus, from this perspective the level of the index i.e. if it is 41 or 49 may not be as important as the actual increase in the index. Two results supports this theory, first note that the short-run coefficients for the entire sample are significant. Secondly, the coefficient for the dummy variable for ISM above 50 ($D_{\text{ISM}>50}$) supports this assumption as it is negative when it is significant implying that an increase in ISM during a recession has a stronger
impact on the stock market than if ISM increases during an expansion. The same interpretation can be done for $D_R$ and $\Delta D_R$. This is intuitively as it can be assumed that moving towards an expansion from an recession is better than simply increasing the production in an expansion which may for example imply danger of overheating the economy.

The momentum analogy is further supported by the results for period 1b i.e. after the financial crisis as the ISM long-run coefficient is significant and positive for this time period. Figure 29 depicts the ISM manufacturing indicator that shows a large spike downwards during the financial crisis. From 2009 and forwards the indicator has consistently been above 50 indicating that more than half of the panel that constitute the purchasing managers’ report an improvement in the manufacturing activity from the previous term. Hence during this period the economy has been recovering from the financial crisis with a semi-upward momentum and which is captured by the ARDL model in the long-run coefficient. Thus following the results the increase in the index and the momentum appears to be more important than the level of the indicator. Consequently when the market is trending the ISM indicator seems to be able to capture the momentum aspect of the market and is from that perspective an important indicator.

To summarize, in general ISM manufacturing has a short-run relationship with S&P500 and should be analyzed from that perspective. Furthermore if the economy is moving out from an recession according to ISM, one may expect an increase in the stock market in the long-run. However when the market is not in a clear bear and bull state one should be careful when interpreting and utilizing the indicator from a long-run perspective.
7.1.7 Process for Evaluating the State of the Economy

Given our results and the corresponding analysis it is possible to conclude that the indicators are different in the way they are related to economic activity and how the practitioner is supposed to interpret them. Due to the characteristics of the indicators this is not surprising as they measure different parts of the economy and are calculated using different methodologies. Therefore investors cannot simply interpret the indicators without a throughout understanding of the context they are used in.

On the basis of our methodology and the consequential results it is possible to extend the general methodology proposed in Figure 2, Section 2.2 to cover the practical evaluation of future stock market movements by introducing additional steps. Figure 30 summarize and combine the general methodology used in this thesis with the analysis given in Section 7.1. Figure 30 can be seen as a concluding framework for evaluating relationships between macroeconomic indicators and a certain stock market. Hence if one wants to investigate the relationship between a certain indicator and a stock market this framework can be used.

Following Figure 30 the process of evaluating macroeconomic indicators can be divided into four steps:

1. In the first step one chooses among other things the stock market under consideration and the time period of choice. Note that as discussed in previous sections the time period of choice will affect the results and accordingly it should be chosen wisely.

2. In the second step one utilize an econometric model to analyze the short-run and long-run relationships between the indicator and the stock market. There are several econometric models that can be used for this purpose and some of them are mentioned in the literature review in Section 3.

3. In terms of evaluating the provided results (step three) from the econometric model our results indicate that it is important to evaluate them from the perspective of macroeconomics e.g. turnings points, development of the housing market and monetary policy. Furthermore in addition to interpreting the level of the indicator when it is released the change and/or the trend can sometimes provide more information i.e. an overall analysis should be conducted.

4. Given that an appropriate analysis has been conducted in accordance with above one may evaluate the potential development of the stock market and act thereafter.
7. Analysis and Discussion of Findings

Figure 30: Refined Mathematical Methodology of State of Economy used in this Study
7.2 Discussion on Model Implications

In this section the measurement of importance and the quality of scientific work is discussed from the perspective of model choices in this thesis.

7.2.1 Measurement of Importance

In this thesis we investigate the relationship between 6 macroeconomic indicators and their relationship to the US stock market index S&P500. A part of that analysis was to cover the importance of the indicators in terms of describing the stock market index. This is of interest as the indicators may have different interpretations of the current state of the economy during a given time period. The basis of the analysis was governed by the results from the ARDL model. ARDL is an econometric model and the results are similar to a regular Ordinary Least Squares (OLS) regression with the corresponding coefficients, standard errors and p-values. The determination of importance regarding the results from a multiple regression model has almost been under investigation since the introduction of the model itself (Budescu 1993). In the light of determining the strongest relationship between the indicators and the stock market there are several different data transformations that can be made. These are discussed below.

In a regression/econometrics context, one can start by examining the relationships between the explanatory variables and the dependent variable. One could argue that the importance of a variable is given by the magnitude of the regression coefficient. This might not turn out to be accurate, as the scale of measurements of the underlying variables is of direct importance. For instance, using years a variable instead of months will multiply the regression coefficient by 12, but the relative importance should remain the same.

Another possibility is to view the p-values, which is the observed statistical significance value of a variable. Contrary to popular belief, there is a distinction between the practical importance and the statistical significance as given by the p-value. This is due to the fact that a small regression coefficient that is measured precisely will have a small p-value, whereas a large regression coefficient that is not measured precisely will have a large p-value.

A third option would be to normalize the regression coefficients by subtracting the mean and dividing by the standard deviation. A correct standardization may however not solve all the problems related to relative importance (Bring 1994) as there is no reason as to why a change of a certain unit in one of the variables standard deviation should correspond to the similar change in another variables standard deviation.

A fourth option would be, as we have done in this thesis, to take the logarithm of the data in order to achieve a percentage interpretation of the coefficient. However as with normalization of the variables there is no reason a 1% change in a variable corresponds to a 1% change in another. For example if building permits increase with 10% regularly and IJC with 1%, a one percentage increase in building permits cannot necessarily be compared with the same increase in IJC.
Hence there are several ways of measuring importance and thus consequently interpreting our results. But overall the importance of the variables should be determined based on the setting in which they are used and from an investor perspective the importance should foremost be based on the relevance of the indicator. Thus the existence of relationships between the variables (short/long-run) are the most important aspects to consider and that the results are unbiased. As the logarithm approach reduce possible heteroscedasticity and provide a simple interpretation of the coefficients we do consider the transformation as sufficient for our purpose.

7.2.2 Quality of Scientific Work

Validity, generalizability and reliability are important aspects of scientific work. According to Blomkvist & Hallin (2015) validity entails studying the right thing. As the chosen indicators are used by analysts to understand the market, we consider that the validity is high. The results was also analyzed qualitatively in order to validate the results from the perspective of advanced macroeconomics. However there are some practical aspects that need to be discussed.

As the time period of choice is between 2000-2016 there are a few disruptions in the market which may or may not affect the results. Given examples are the dot-com bubble in the early 2000s, the housing bubble in the US between 1997-2006, the following Financial crisis after the bankruptcy of Lehman Brothers in 2008 and the introduction of Quantitative Easing (QE) by the U.S. Federal Reserve in late 2008. The inclusion of financial events in time series is fairly common as events like the above occur frequently irrespective of the time period. Furthermore, as the time period 2000-2016 was divided into two different time periods in order to answer the contemplated research questions the impact of the events should increase for each sub-sample in relation to the entire sample. The uncertainty created by sudden unusual market reactions can be captured in the residuals and/or coefficient instability in the mean or the variance. To assure non-biased coefficients several diagnostic tests were performed including the CUSUM and CUSUMSQ tests for parameter instability in the mean and the variance. The results from the econometric model was also discussed in relation to the market conditions to conclude if they have affected the results or not. We are therefore confident that our results are not affected by events and/or are biased.

The choice of indicators may affect our results in terms of omission bias. In general, the inclusion of addition variables can increase the complexity of the results i.e. more relationships can be found, but at the cost of potential biases and a more difficult interpretation. In order to cover a satisfactory part of the economy the indicators are divided into certain certain sub-groups, thus reducing the effect of omitted variables. This is described in detail in Section 4. Overall one may propose that indicators describing the same event or activity e.g. unemployment, industrial production and more may have the same effect on the market as they are most likely strongly correlated. Hence we do not consider our choice of indicators as a problem.
The generalizability of the results is fairly high within the context of the US stock market but since economies and accordingly the stock markets can differ between countries due to e.g. different specialties and structures the results may not be sufficiently generalized to other countries. For similar western countries it is possible that the results can be fairly generalized but further research is necessary. As the purpose of this thesis is to investigate the US stock market, we do not see the generalizability as a fallacy as the major stock index in the US, S&P500 is used. S&P500 is often used as a proxy for the US stock market as it contains the 500 largest publicity owned companies in the US. Furthermore S&P500 usually has a common trend with other major indices in the US such as NASDAQ and Dow Jones as they partly contain the same companies. Hence it can be assumed that the results are fairly generalizable for some other US stock market indices.

The reliability of a study relates to the possibility of other researchers to reproduce the study under the same circumstances (Collis & Hussey 2014) and acquire the same results. As the thesis is based on public data and well-known econometric methods we expect other researchers to be able to replicate our research and obtain similar results. Thus we do consider the reliability to be high.
8 Conclusion and Implications

In the final main section of this thesis a summarized conclusion is given on the basis of the results and the corresponding analysis. Finally a suggestion for further research is provided.

In this thesis we investigate the relationship between macroeconomic indicators such as building permits, Michigan consumer sentiment index, initial jobless claims (IJC), personal spending, M1 money supply, ISM manufacturing and US stock market index S&P500. Macroeconomic indicators are important as they provide a tool for analyzing the current and future state of the economy. As the stock market is a concurrent part of the economy, indicators are used in order to evaluate stock market investments. Consequently the indicator must function according to its purpose and be used properly otherwise the investor may experience large capital loses. The purpose of this thesis was therefore to investigate the short-run and long-run relationships between the US stock market index S&P500 and the six selected macroeconomic indicators during the beginning of the 21th century. In order to achieve the purpose we sought to answer the research questions below by using the Autoregressive Distributed Lags model (ARDL) as it has several advantages in relation to comparable methods.

RQ 1.1 What are the short and long-run relationships between our chosen set of macroeconomic indicators and the US stock market?

RQ 1.2 Do the set of macroeconomic indicators have different relationships with the stock market during different time periods?

RQ 1.3 Which and when are the macroeconomic indicators most important for describing the stock market development?

The results from the F-bounds test show evidence for a long-run relationship between the variables i.e. they move together in the long-run. For all the time periods the results are non-biased according to the aforementioned diagnostic tests. However for the last period IJC and M1 became strongly related after the financial crisis. If this relationship is due to monetary policy or simply the market dynamics remain unknown and can be a topic for further research.

Initial jobless claims seem to be the most important indicator in our sub-set of indicators as it always has a negative and significant relationship with the stock market in both the long-run and the short-run. The negative coefficient is due to IJCs close connection to the economic activity through overall confidence and spending behavior and is therefore always seemingly important. The M1 money supply has a positive long-run relationship with the stock market most likely due to its negative connection to interest rates. Comparing our results with previous research (Humpe & Macmillan 2009), aggressive monetary policy e.g. Quantitative Easing and consequently very low interest rates may be the underlying cause of the relationship given our time period. Furthermore, unlike IJC and M1 the building permits coefficients contradict general macroeconomic theory as it is negative. However there have been time periods starting from 2000 where the housing
market according to the building permits indicator has been independent from the stock market and been moving in an opposite direction. This suggest that building permits may e.g. increase due to certain dynamics on the housing market rather than in the economy as a whole. Therefore it is vital to consider the underlying dynamics of the housing market before interpreting the indicator. The Michigan consumer sentiment index has a positive but shifting significance on the long-run and short-run coefficients depending on the time period which may possible be due to a combination of sample dynamics and specific events. Given the results the indicator seems to be most appropriate in turning points of the economy and to determine whether the increase/decrease in the market will continue. Personal spending always has a positive relationship with the stock market which is intuitively as household spending account for roughly 2/3 of GDP (Baumohl 2012). The ISM manufacturing index is in general important for measuring the short-run dynamics but our results indicate that when the economy is in a clear state of expansion or recession the long-run dynamics are also captured by the indicator. This suggests that the actual percentage change of the indicator level is in general more important than the actual level. The results are summarized in Table 11 where ✓ implies that a significant relationship was found on at least a 5% level and the +/− corresponds to sign of the relationship.

Table 11: Summary of the results. ✓ = Significance, X = No significance, + = Positive relationship, − = Negative relationship. Source: Authors computation

<table>
<thead>
<tr>
<th>Variables</th>
<th>Period 1</th>
<th>Period 1a</th>
<th>Period 1b</th>
</tr>
</thead>
<tbody>
<tr>
<td>ISM Manufacturing</td>
<td>✓ (+)</td>
<td>X</td>
<td>✓ (+)</td>
</tr>
<tr>
<td>Michigan Consumer</td>
<td>✓ (+)</td>
<td>X</td>
<td>✓ (+)</td>
</tr>
<tr>
<td>Initial Jobless Claims</td>
<td>✓ (−)</td>
<td>✓ (−)</td>
<td>✓ (−)</td>
</tr>
<tr>
<td>Building Permits</td>
<td>X</td>
<td>✓ (−)</td>
<td>✓ (+)</td>
</tr>
<tr>
<td>Personal Spending</td>
<td>X</td>
<td>✓ (+)</td>
<td>✓ (+)</td>
</tr>
<tr>
<td>M1 Money Supply</td>
<td>X</td>
<td>✓ (+)</td>
<td>✓ (+)</td>
</tr>
</tbody>
</table>

The overall conclusion is that the chosen indicators have different characteristics depending on the current dynamics of the stock market, economic state and other related markets. To illustrate how one can utilize our results and the corresponding analysis, we provide two examples. The assumption underlying these examples is that the relationships continue to exist and that it is possible to take long or short positions whenever one desires. First, the practical implication of our results to an investor can be seen in ISM Manufacturing for instance, where the indicator does not have a significant relationship with S&P500 in period 1a, in a time when the economy was expanding. Using ISM Manufacturing during an expansive economy will therefore be of limited use according to our results. Secondly, according to our results the M1 Money Supply has a long-run relationship with the stock market during all time periods under consideration. Hence, assuming that the current relationship continue to exist, an investor e.g. a global asset allocator can adjust his portfolio depending on monetary policy announcements by the US Federal Reserve. For example if FED intend to increase the money supply the investor may increase the exposure towards US equities. The results in the previous paragraph together with Table 11 for the other indicators can be used by an investor in the same manner as described for ISM Manufacturing and M1 Money Supply.
To summarize, a thorough analysis of the indicators and their relationship to various parts of the economy is thus needed to be done before they are used. The practical implication for investors is that different indicators are of limited use depending on the current market dynamics and investors must evaluate the underlying premises of the development of the indicator rather than interpreting a specific publication of the indicator.

8.1 Suggestion for Further Research

This study investigates the short-run and long-run relationship between our chosen macroeconomic indicators and the US stock market SP&500. As mentioned in Section 6 the relationships were evident for many indicators but one interesting aspect to consider is the positive significant long-run coefficient for money supply which is not similar to previous research. One possible explanation for this is the introduction of aggressive monetary policy in terms of QE and low interest rates. A suggestion for further research is therefore to investigate if the money supply relationship with the stock market is due to monetary policy e.g. QE or some market dynamic.

Furthermore for the period between 2009-2016 the variables M1 and IJC seem to be strongly collinear. Whether this is an effect of the sample size or the general dynamic of the financial markets is outside the scope of this thesis. However for further research it can be interesting to investigate if the recent relationship is due to e.g. Quantitative Easing or some other direct/indirect relationship. The research may provide further knowledge of the implication of QE and if it is a good tool for altering the employment level.

Additionally as six indicators were investigated for the US market, possible further research may investigate if the relationship remain for different countries. Even though, studies of different countries have shown to produce fairly different results, it still remain relevant. As by analyzing different countries one may gain further knowledge of why the relationships exists.

Finally other complementing and/or substituting indicators can be analyzed and additional statistical methods can be utilized. For example one may compare ISM manufacturing and its newer substitute the Markit Manufacturing index to assess if it is an better indicator. Furthermore, one could perform a prediction study rather than a inference study whereby one utilize our model with possibly more variables to predict S&P500. Methods to consider could be back-testing och out-of-sample regressions.
References


References


## A Appendix - Additional Tables

### A.1 Tables for Period 1

Tables for Period 1.

Table 12: ARDL for the entire period. $R^2 = 32.84\%$

<table>
<thead>
<tr>
<th>Long-run</th>
<th>Independent Variable</th>
<th>Coefficient</th>
<th>Std.error</th>
<th>P-value</th>
<th>95% Confidence interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>ISM</td>
<td>0.176</td>
<td>0.322</td>
<td>0.586</td>
<td></td>
<td>[-0.460,0.811]</td>
</tr>
<tr>
<td>MC</td>
<td>0.300</td>
<td>0.219</td>
<td>0.173</td>
<td></td>
<td>[-0.133,0.734]</td>
</tr>
<tr>
<td>IJC</td>
<td>-1.160</td>
<td>0.195</td>
<td>0.000</td>
<td></td>
<td>[-1.544,-0.776]</td>
</tr>
<tr>
<td>BP</td>
<td>-0.270</td>
<td>0.087</td>
<td>0.002</td>
<td></td>
<td>[-0.441,-0.099]</td>
</tr>
<tr>
<td>PS</td>
<td>0.180</td>
<td>0.091</td>
<td>0.049</td>
<td></td>
<td>[0.000,0.359]</td>
</tr>
<tr>
<td>M1</td>
<td>0.388</td>
<td>0.107</td>
<td>0.000</td>
<td></td>
<td>[0.177,0.598]</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Short-run</th>
<th>Independent Variable</th>
<th>Coefficient</th>
<th>Std.error</th>
<th>P-value</th>
<th>95% Confidence interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta SP500_{t-1}$</td>
<td>-0.129</td>
<td>0.080</td>
<td>0.107</td>
<td></td>
<td>[-0.286,0.028]</td>
</tr>
<tr>
<td>$\Delta SP500_{t-2}$</td>
<td>-0.276</td>
<td>0.076</td>
<td>0.000</td>
<td></td>
<td>[-0.426,-0.126]</td>
</tr>
<tr>
<td>$\Delta ISM_t$</td>
<td>0.224</td>
<td>0.108</td>
<td>0.04</td>
<td></td>
<td>[0.010,0.437]</td>
</tr>
<tr>
<td>$\Delta ISM_{t-1}$</td>
<td>0.235</td>
<td>0.097</td>
<td>0.017</td>
<td></td>
<td>[0.043,0.427]</td>
</tr>
<tr>
<td>$\Delta ISM_{t-2}$</td>
<td>0.181</td>
<td>0.091</td>
<td>0.05</td>
<td></td>
<td>[0.000,0.360]</td>
</tr>
<tr>
<td>$\Delta MC_t$</td>
<td>0.212</td>
<td>0.061</td>
<td>0.001</td>
<td></td>
<td>[0.091,0.332]</td>
</tr>
<tr>
<td>$\Delta IJC_t$</td>
<td>-0.204</td>
<td>0.059</td>
<td>0.001</td>
<td></td>
<td>[-0.320,-0.088]</td>
</tr>
<tr>
<td>$\Delta BP_t$</td>
<td>0.008</td>
<td>0.066</td>
<td>0.9</td>
<td></td>
<td>[-0.122,0.139]</td>
</tr>
<tr>
<td>$\Delta PS_t$</td>
<td>0.014</td>
<td>0.008</td>
<td>0.109</td>
<td></td>
<td>[-0.003,0.030]</td>
</tr>
<tr>
<td>$\Delta M1_t$</td>
<td>-0.141</td>
<td>0.254</td>
<td>0.579</td>
<td></td>
<td>[-0.642,0.360]</td>
</tr>
<tr>
<td>$ECM_{t-1}$</td>
<td>-0.169</td>
<td>0.039</td>
<td>0.000</td>
<td></td>
<td>[-0.245,-0.092]</td>
</tr>
<tr>
<td>$D_{ism&gt;50}$</td>
<td>-0.027</td>
<td>0.012</td>
<td>0.021</td>
<td></td>
<td>[-0.050,-0.004]</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.524</td>
<td>0.843</td>
<td>0.535</td>
<td></td>
<td>[-1.140,2.189]</td>
</tr>
</tbody>
</table>
A.2 Tables for Period 1a

Tables for Period 1a.

Table 13: ARDL for the period 1a. $R^2 = 39.50$

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Coefficient</th>
<th>Std.error</th>
<th>P-value</th>
<th>95% Confidence interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>ISM</td>
<td>-0.042</td>
<td>0.404</td>
<td>0.917</td>
<td>[-0.845,0.7615]</td>
</tr>
<tr>
<td>MC</td>
<td>0.379</td>
<td>0.322</td>
<td>0.243</td>
<td>[-0.262,1.021]</td>
</tr>
<tr>
<td>IJC</td>
<td>-1.053</td>
<td>0.216</td>
<td>0.000</td>
<td>[-1.482,-0.624]</td>
</tr>
<tr>
<td>BP</td>
<td>-0.225</td>
<td>0.158</td>
<td>0.159</td>
<td>[-0.538,0.0893]</td>
</tr>
<tr>
<td>PS</td>
<td>0.309</td>
<td>0.132</td>
<td>0.022</td>
<td>[0.046,0.571]</td>
</tr>
<tr>
<td>M1</td>
<td>0.896</td>
<td>0.425</td>
<td>0.038</td>
<td>[0.051,1.1741]</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Coefficient</th>
<th>Std.error</th>
<th>P-value</th>
<th>95% Confidence interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta ISM_t$</td>
<td>0.125</td>
<td>0.129</td>
<td>0.333</td>
<td>[-0.130,0.381]</td>
</tr>
<tr>
<td>$\Delta MC_t$</td>
<td>0.119</td>
<td>0.074</td>
<td>0.113</td>
<td>[-0.028,0.266]</td>
</tr>
<tr>
<td>$\Delta IJC_t$</td>
<td>-0.212</td>
<td>0.067</td>
<td>0.002</td>
<td>[-0.347,-0.077]</td>
</tr>
<tr>
<td>$\Delta BP_t$</td>
<td>-0.197</td>
<td>0.093</td>
<td>0.038</td>
<td>[-0.382,-0.012]</td>
</tr>
<tr>
<td>$\Delta BP_{t-1}$</td>
<td>-0.178</td>
<td>0.099</td>
<td>0.076</td>
<td>[-0.378,0.019]</td>
</tr>
<tr>
<td>$\Delta PS_t$</td>
<td>0.028</td>
<td>0.094</td>
<td>0.004</td>
<td>[0.009,0.047]</td>
</tr>
<tr>
<td>$\Delta M1_t$</td>
<td>-0.318</td>
<td>0.338</td>
<td>0.349</td>
<td>[-0.992,0.354]</td>
</tr>
<tr>
<td>$ECM_{t-1}$</td>
<td>-0.187</td>
<td>0.058</td>
<td>0.002</td>
<td>[-0.303,-0.071]</td>
</tr>
<tr>
<td>$D_{ism&gt;50}$</td>
<td>-0.031</td>
<td>-0.013</td>
<td>0.02</td>
<td>[-0.057,0.005]</td>
</tr>
<tr>
<td>$DR$</td>
<td>0.196</td>
<td>0.082</td>
<td>0.02</td>
<td>[0.032,0.360]</td>
</tr>
<tr>
<td>$\Delta DR$</td>
<td>0.104</td>
<td>0.0283</td>
<td>0.000</td>
<td>[0.047,0.160]</td>
</tr>
<tr>
<td>Intercept</td>
<td>-2.172</td>
<td>2.286</td>
<td>0.345</td>
<td>[-6.720,0.2374]</td>
</tr>
</tbody>
</table>

Table 14: ADF test adjusted for financial crisis (Period 1a). *,**,*** represents a significance level of 5%, 2.5% and 1% respectively. SIC is the optimal lag. The values in parenthesis are the MacKinnon p-values and the remaining numbers are the test-statistics. Source: Authors computation

<table>
<thead>
<tr>
<th>Variables</th>
<th>SIC</th>
<th>ADF Test - No Trend</th>
<th>ADF Test - Trend</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>SP500</td>
<td>1</td>
<td>-1.551(0.5079)</td>
<td>-1.762(0.7228)</td>
<td>I(1)***</td>
</tr>
<tr>
<td>ISM Manufacturing</td>
<td>1</td>
<td>-1.841(0.3060)</td>
<td>-1.826(0.6921)</td>
<td>I(1)***</td>
</tr>
<tr>
<td>Michigan Consumer</td>
<td>1</td>
<td>-2.338(0.1926)</td>
<td>-2.972(1.400)</td>
<td>I(1)***</td>
</tr>
<tr>
<td>IJC</td>
<td>1</td>
<td>-1.885(0.3392)</td>
<td>-1.882(0.6641)</td>
<td>I(1)***</td>
</tr>
<tr>
<td>Building Permits</td>
<td>2</td>
<td>1.956 (0.9986)</td>
<td>1.484 (1.000)</td>
<td>I(1)***</td>
</tr>
<tr>
<td>Personal Spending</td>
<td>1</td>
<td>-9.941 (0.000)</td>
<td>-9.949(0.000)</td>
<td>I(0)**</td>
</tr>
<tr>
<td>M1</td>
<td>2</td>
<td>-0.599(0.8712)</td>
<td>-1.126(0.9246)</td>
<td>I(1)***</td>
</tr>
</tbody>
</table>
A.3 Tables for Period 1b

Tables for Period 1b.

Table 15: ARDL for the period 1b. $R^2 = 31.52\%$

Long-run

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Coefficient</th>
<th>Std.error</th>
<th>P-value</th>
<th>95% Confidence interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>ISM</td>
<td>0.627</td>
<td>0.222</td>
<td>0.006</td>
<td>[0.184,1.07]</td>
</tr>
<tr>
<td>MC</td>
<td>0.455</td>
<td>0.150</td>
<td>0.004</td>
<td>[0.155,0.756]</td>
</tr>
<tr>
<td>BP</td>
<td>0.031</td>
<td>0.144</td>
<td>0.832</td>
<td>[-0.257,0.318]</td>
</tr>
<tr>
<td>PS</td>
<td>0.037</td>
<td>0.054</td>
<td>0.489</td>
<td>[-0.069,0.144]</td>
</tr>
<tr>
<td>M1</td>
<td>0.909</td>
<td>0.164</td>
<td>0.000</td>
<td>[0.581,1.236]</td>
</tr>
</tbody>
</table>

Short-run

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Coefficient</th>
<th>Std.error</th>
<th>P-value</th>
<th>95% Confidence interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta ISM_t$</td>
<td>0.278</td>
<td>0.174</td>
<td>0.115</td>
<td>[-0.070,0.626]</td>
</tr>
<tr>
<td>$\Delta MC_t$</td>
<td>0.086</td>
<td>0.092</td>
<td>0.352</td>
<td>[-0.097,0.269]</td>
</tr>
<tr>
<td>$\Delta BP_t$</td>
<td>0.203</td>
<td>0.092</td>
<td>0.032</td>
<td>[0.018,0.388]</td>
</tr>
<tr>
<td>$\Delta BP_{t-1}$</td>
<td>0.127</td>
<td>0.088</td>
<td>0.152</td>
<td>[-0.0479,0.302]</td>
</tr>
<tr>
<td>$\Delta PS_t$</td>
<td>0.007</td>
<td>0.016</td>
<td>0.689</td>
<td>[-0.026,0.0389]</td>
</tr>
<tr>
<td>$\Delta M1_t$</td>
<td>0.704</td>
<td>0.375</td>
<td>0.065</td>
<td>[-0.0461,1.453]</td>
</tr>
<tr>
<td>$ECM_{t-1}$</td>
<td>-0.453</td>
<td>0.106</td>
<td>0.000</td>
<td>[-0.666,-0.240]</td>
</tr>
<tr>
<td>$D_{ism&gt;50}$</td>
<td>0.002</td>
<td>0.024</td>
<td>0.940</td>
<td>[-0.0470,0.050]</td>
</tr>
<tr>
<td>Intercept</td>
<td>-10.549</td>
<td>3.310</td>
<td>0.002</td>
<td>[-17.161,-3.936]</td>
</tr>
</tbody>
</table>

Table 16: IJC and MC relationship Comparison. Source: Authors Computations

<table>
<thead>
<tr>
<th>Period 1</th>
<th>Period 1a</th>
<th>Period 1b</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(IJC)</td>
<td>ln(M1)</td>
<td>ln(IJC)</td>
</tr>
<tr>
<td>ln(M1)</td>
<td>-1.863**</td>
<td>0.889</td>
</tr>
<tr>
<td>$\Delta ln(IJC)_t$</td>
<td>-0.444</td>
<td>-0.874***</td>
</tr>
<tr>
<td>$\Delta ln(IJC)_{t-1}$</td>
<td>-0.200***</td>
<td>-0.393**</td>
</tr>
<tr>
<td>$\Delta ln(M1)_t$</td>
<td>-0.038</td>
<td>-0.284</td>
</tr>
<tr>
<td>$\Delta ln(M1)_{t-1}$</td>
<td>-0.297***</td>
<td>1.922***</td>
</tr>
<tr>
<td>$\Delta ln(M1)_{t-2}$</td>
<td>-0.087</td>
<td>1.757***</td>
</tr>
<tr>
<td>$\Delta ln(M1)_{t-3}$</td>
<td>-0.250***</td>
<td>1.716***</td>
</tr>
<tr>
<td>$ECM_{t-1}$</td>
<td>0.008**</td>
<td>-0.137**</td>
</tr>
<tr>
<td>Constant</td>
<td>1.016*</td>
<td>-0.315***</td>
</tr>
</tbody>
</table>

$R^2$ 7.312 % 20.550% 16.492% 21.626% 38.211% 5.207%

F-Test 2.358 4.661 3.2 1.288 9.689*** 0.429
The critical values below.

Table 17: Critical values for IJC and M1 comparison. Source: Pesaran et al. (2001)

<table>
<thead>
<tr>
<th>Critical values</th>
<th>5%</th>
<th>2.5%</th>
<th>1%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Limits</td>
<td>[4.94,5.73]</td>
<td>[5.77,6.68]</td>
<td>[6.84,7.84]</td>
</tr>
</tbody>
</table>
B Appendix - Additional Figures

B.1 Data

Figure 31: The development of Michigan Consumer and IJC. Source: Bloomberg

Figure 32: The development of ISM manufacturing and Building Permits. Source: Bloomberg

Figure 33: The development of M1 and Personal Spending. Source: Bloomberg, Macrobond
B.2 First Differenced Data

Figure 34: First Difference of Michigan Consumer and IJC. Source: Bloomberg

Figure 35: First Difference of ISM manufacturing and Building Permits. Source: Bloomberg

Figure 36: First Difference of M1 and Personal Spending. Source: Bloomberg, Macrobond
B.3 Predictions

![Figure 37: Prediction vs Actual S&P500 Values for Period 1. Source: Authors Computations](image1)

![Figure 38: Prediction vs Actual S&P500 Values for Period 1a. Source: Authors Computations](image2)
Figure 39: Prediction vs Actual S&P500 Values for Period 1b. Source: Authors Computations

Figure 40: Out-of-Sample Prediction vs Actual S&P500 Values. Source: Authors Computations
B.4 ACF Plots

An additional test for autocorrelation can be seen below. Figure 41-43 are the autocorrelation function (ACF) plots of the residuals during each time period. The plot can provide evidence for randomness or autocorrelation in the residuals. In an ACF plot for residuals, it is expected that 95 % of the points are within the 95% confidence intervals (red dotted lines in Figure 41-43) in order for the residuals to outcomes of white noise i.e. not autocorrelated.

Figure 41: ACF Plot Residuals Period 1. Source: Authors Computations

Figure 42: ACF Plot Residuals Period 1a. Source: Authors Computations

Figure 43: ACF Plot Residuals Period 1b. Source: Authors Computations