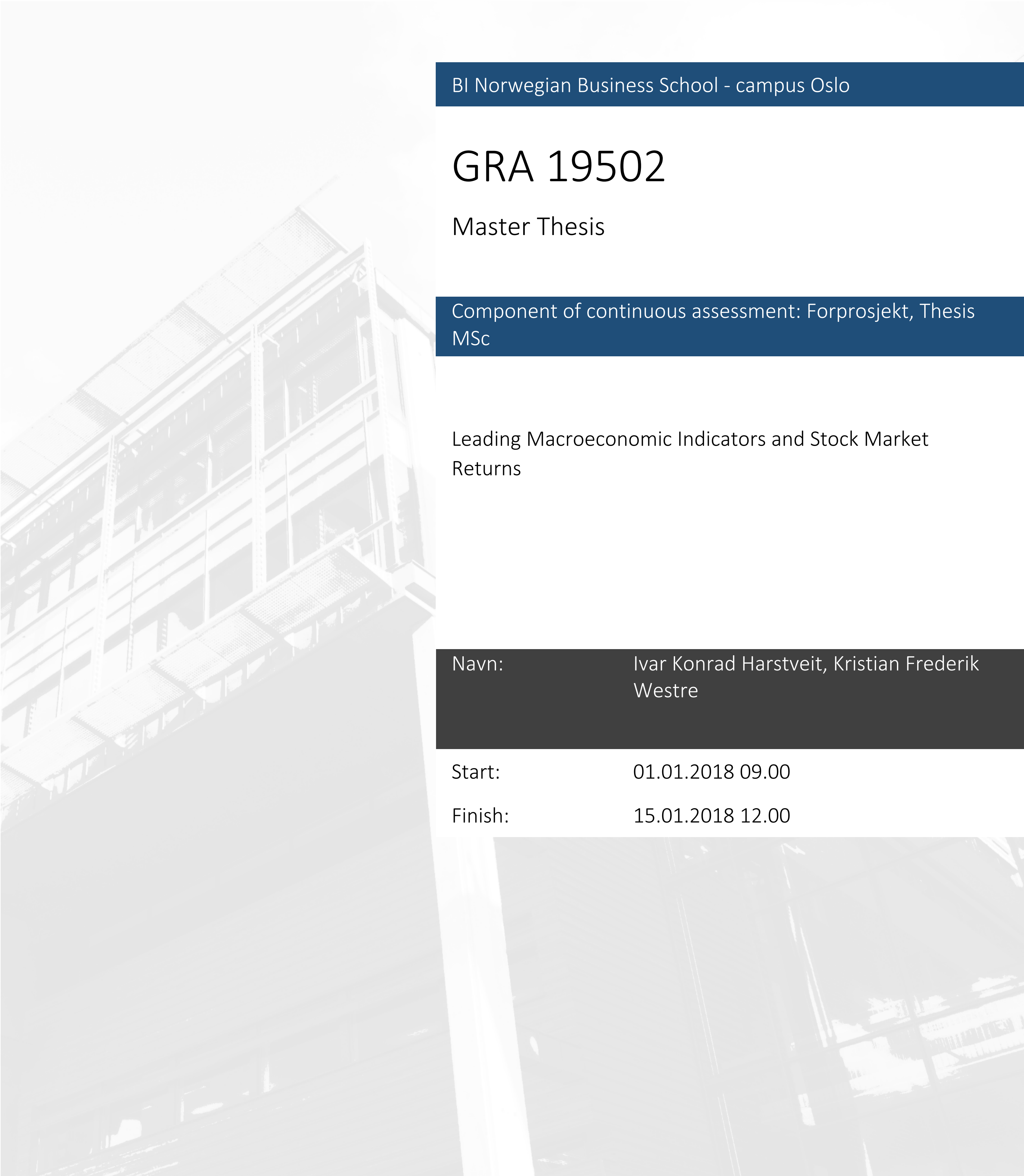

BI Norwegian Business School - campus Oslo

GRA 19502

Master Thesis

Component of continuous assessment: Forprosjekt, Thesis MSc

Leading Macroeconomic Indicators and Stock Market Returns

Navn: Ivar Konrad Harstveit, Kristian Frederik Westre

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Study Programme

MSc in Business, Major in Finance

Title

"Leading Macroeconomic Indicators and Stock Market Returns"

Supervisor

Alessandro Graniero

Contents

Abstract:

The area of study will be investments, with focus on predicting stock market returns. We want to study if information contained in a specific set of leading macroeconomic indicators contradicts the semi-strong market hypothesis. Furthermore, we intend to test if leading macroeconomic indicators at time (t) predict stock market returns at time (t+1). The time lag (t+1) is considered short term, 1-3 months. To test for predictability, we will use ordinary least squares (OLS) regression models, both univariate, bivariate and multivariate. The aim of the thesis is to build a model that shows the relationship between the leading economic indicators and GDP, followed by an analysis of the relationship between growing GDP and S&P 500 returns. Statistical evidence such as correlation, will influence whether we will be able to conclude for predictability.

Chapter 1: Introduction and motivation:

The question to be studied:

Does information contained in leading macroeconomic indicators contradict the semi-strong efficient market hypothesis?

Motivation:

The motivation behind the study, is to examine the relationship between leading macroeconomic indicators and GDP, and thus be able to predict stock market returns. Since the millennial shift, we have experienced two severe recessions, and two severe market downturns. These downturns were associated with the information technology sector (2000-2002), and secondly the housing sector (2008-2009), However, corrections were not contained within these sectors, and affected the broader market. For an investor, it would benefit the risk-return tradeoff of investing in the stock market, if able to predict recessions. Furthermore, being able to forecast the end of a recession, may also benefit the investor to time re-entry in the market.

Our Contribution:

We want to use leading macroeconomic indicators, which in this case act as a proxy for expectations regarding the future variable. The future variable could be GDP growth, or variables correlated with GDP such as retail sales, housing starts, and industrial production, etc. These variables are what are called lagging indicators. By using this, we can see if there is a relationship between the expectation formed by the leading indicators at time (t) and the actual outcome, shown by the lagging indicators at time (t+1).

We want to be specific, with short-term forecasting. In this regard, short-term would implies a 1-3 months' time-horizon. Furthermore, we will focus on specific leading macroeconomic indicators, such as the Institute For Supply Management (ISM) Manufacturing Report on Business (ROB) and Non-Manufacturing Report On Business. Also, we will use the Survey of Consumers Sentiment, by the University of Michigan. Lastly, we will focus on the monthly Building Permits Survey by the United States Census Bureau.

Addressing the issue:

We are going to make an empirical study where we obtain and analyze macroeconomic data in order to reveal the relationship between a specific combination of leading economic indicators and their explanatory power on predicting stock market returns. We will obtain the data from databases such as Bloomberg and use MATLAB to analyse the data.

Furthermore, we will proceed with the following structure: Obtaining historical data and build univariate, bivariate and multivariate OLS regression models, in order to test and examine various historical relationships between the explanatory variables and the explained variable.

Summary of the results:

By running empirical studies, we will obtain and analyse results. The findings may either be in line or contradict our hypothesis. However, some results may turn out to be ambiguous or insignificant.

Chapter 2: Literature Review

Relevant Articles:

A study conducted by Li, Wang, Yu (2017) highlights the relationship between "Aggregate Expected Investment Growth" (AEIG) and stock market returns. The motivation behind the study is to analyse the return predictability of AEIG on future stock market returns. (Li, Wang, Yu (2017) propose a bottom-up measure of aggregate investment plans, referred to as the aggregate expected investment growth (AEIG), by aggregating the firm-level expected investment growth (EIG). The researchers conducted several empirical studies and ran both univariate, bivariate and multivariate regressions where the researchers controlled for other popular macroeconomic return predictors such as the Treasury bill rate, term spread, default spread, market return variance etc.

In the paper, the researchers document that AEIG is a strong predictor of future stock market returns. An increase in AEIG is associated with declines in the stock market, with an adjusted in-sample R^2 of 18.5% and an out-of-sample R^2 of 16.3% at the one-year horizon. The return predictive power is not subsumed by other macroeconomic variables that are well-known for predicting market returns (Li, Wang, Yu, 2017).

The researchers also found that AEIG predicts macroeconomic activities such as GDP-growth, consumption growth and industrial production growth. Economic growth tends to be positive in the first two quarters after periods of high AEIG, following recessions in the subsequent two to three years. In the predictive regressions for GDP and aggregate consumption growth, high AEIG is associated with strong GDP and consumption growth in the subsequent year, following a strongly negative coefficient on AEIG in the second year. Therefore, high AEIG leads both stock market declines and business cycle peaks (Li, Wang, Yu, 2017).

According to Li, Wang, Yu (2017), the main finding that AEIG negatively predicts stock returns can be consistent with both rational and behavioural explanations. On the rational side, when aggregate cost of capital falls due to either lower price of risk or a lower quantity of risk, firms initiate more investment plans and AEIG increases. This is followed by lower stock returns on average, corresponding to a risk based explanation for the predictability of AEIG. On the behavioural side, investors can be overly optimistic about the aggregate economy and overvalue the stock market, while managers initiate to many investment plans either because they share this sentiment with investors or because they take advantage of this overvaluation by issuing more equity. This mispricing is then corrected by disappointing future economic fundamentals when investors realize their prior expectation errors, giving rise to the negative predictive ability of AEIG for market returns.

Similar to our intended research Li, Wang, Yu (2017), use leading indicators which are based on future expectations to predict stock market returns. In addition, the researchers analyse the relationship between AEIG and various macroeconomic metrics such as GDP-growth, consumption-growth and industrial production growth. This makes the paper relevant to our research as we intend to apply a similar kind of structure where the leading macroeconomic indicators we intend to use are closely connected to the macroeconomic metrics such as GDP-growth, consumption growth and industrial production growth.

Another research paper relevant for our research question is the paper "Investment Plans and Stock Returns" by Lamont (2000). Lamont (2000) investigates the hypothesis that when the discount rate falls, investment should rise. Thus, with time-varying discount rates and instantly changing investment, investment should positively covary with current stock returns and negatively covary with future stock returns. However, according to Lamont (2000) post-war annual aggregate U.S. data on stock returns and nonresidential investment growth contradict these implications.

The research conducted by Lamont (2000) concludes that investment and stock returns have a significant negative contemporaneous covariation, and investment and future stock returns have a covariation that is not statistically different from zero. According to Lamont (2000), this negative contemporaneous correlation between investment and stock returns can be explained with investment lags and time varying-risk premia. In order to test the hypothesis that investment lags are responsible, Lamont (2000) focuses on planned investments. The investment plans are from a survey of capital expenditure plans conducted by the U.S. Commerce Department between 1947 and 1993. According to Lamont (2000), plans explain more than three quarters of the variation in real annual aggregate investment growth. Furthermore, they have substantial forecasting power for excess stock returns, showing that time-varying risk premia affect investment.

Similar to the research by Li, Wang, Yu (2017) and the research we intend to do, Lamont (2000) uses leading macroeconomic indicators, such as investment plans to predict stock market returns. In addition, the investment plans data Lamont (2000) used is a survey conducted by a government agency. This makes the data similar to ours as we also intend to use some data which are surveys conducted by a government agency, like the U.S Census Bureau Building Permits Survey.

Knowledge gap:

The intention behind the studies presented above, like our own, is to use a set of explanatory variables to predict stock market returns. The main differences lie within the data used and the motivation behind the specific data.

Lamont (2000) uses OLS regressions to predict stock returns using planned investment, actual investment, actual lagged investment, and the equity share of total equity issues to the sum of total debt plus total equity issues. The dependent variable is real stock returns (i.e. the total return for one year on the S&P Composite Index minus the growth in the CPI during the same year).

Li, Wang, Yu (2017) use the log of future cumulative excess market returns (i.e. total return of the S&P Composite Index minus the risk-free rate) as the dependent variable and aggregate expected investment growth, log of dividend yield, Lettau and Ludvigson (2001)'s consumption-wealth ratio, term spread, stock variance, default yield spread, inflation, detrended T-bill rate, surplus ratio, investment-to-capital ratio, and Jones and Tuzel (2013)'s log of the ratio of new orders to shipment.

The knowledge gap existent in the literature is based on the fact that no academic research has been conducted on the ISM Manufacturing ROB, which is our main explanatory variable. In addition, the various explanatory variables we focus on are leading economic indicators that form expectations about economic attributes within specific sectors, that on an aggregate level cover a significant part of the U.S. GDP. The intention behind our research is to use macroeconomic indicators that are highly correlated with U.S. GDP to predict the S&P 500. For instance, the ISM Manufacturing ROB covers the manufacturing industry, the ISM Non-Manufacturing ROB covers the service industry, The University of Michigan

Consumer Sentiment Indicator covers consumers and the Census Bureau Building Permits Indicator covers the housing sector. This indicator gives indirectly also insights into the health and liquidity of the U.S banking sector as debt financing plays an important role with in the housing sector. Furthermore, this approach is different compared to Lemont (2000) and Li, Wang, Lu (2017) since they focus specifically on investment growth to predict stock market returns, rather than the growth in the aggregate economy.

Appropriateness of our chosen methodology and data:

The methodologies in both articles are relevant since they use a set of explanatory variables to predict an explained variable, which in both articles is annual stock returns on the S&P 500. They use various forms of OLS regressions like univariate, bivariate and multivariate regressions, where they use a set of control variables to analyse the predictability of their main variable, in order to do their studies. In addition, when controlling for other variables, test of individual and joint significance of the regressors are performed to analyse the explanatory power of various combinations of regressors.

Since the motivation behind our research thesis is to study the predictability a specific set of leading macroeconomic indicators has on the returns of the S&P 500, it seems reasonable to use a similar type of methodology to conduct our intended research.

The U.S Commerce department discontinued the investment survey in 1993 (Lamont, 2000). This makes it impossible to use the investment plans survey today as a variable to predict stock market returns.

The AEIG variable that Li, Yu and Wang (2017) use must be estimated in several steps. In the first step, the researchers, run for each year a panel predicate regression of the investment growth in the subsequent year on momentum (prior-2-12-month stock returns), q, and cash flow. Specifically, investment growth is the growth rate of investment expenditure, momentum is the (-12.-2) 11-month cumulative stock return from the fiscal year end, q is the market value of the firm (sum of market equity, long-term debt, and preferred stock minus inventories and deferred taxes) divided by capital, and cash flow is the sum of depreciation and income before extraordinary items divided by capital. In the second step, the researchers calculate the monthly firm-level expected investment growth (EIG) as the out-of-sample predicted value of investment growth based on the estimated coefficients to date and the current values of momentum, q, and cash flow. AEIG is then defined as the value-weighted average of firm-level EIG with the market value of equity at the end of the previous month as the weight (Li, Wang, Yu, 2017). This may seem as a complicated and tedious process which is difficult to generalize towards the average retail investor.

The benefit of our research data is that it is publicly available and doesn't need to be estimated like for instance the AEIG data. This makes it easier for the average investor to start using our proposed leading economic indicators for attempting to predict the stock market on his own. In addition, our data is updated on a monthly basis which makes it available at a higher frequency than for instant the investment plans survey data that was used by Lamont (2000). Another important feature regarding our data is that for our main explanatory variable, the ISM Manufacturing ROB, the data dates back to 1948 which gives us a sample size of over 840 monthly observations. In addition, the sample size for our controlling variables like the University of Michigan Consumer Sentiment Index and the Census Bureau Building Permits Survey also both date back to the 1950s and 1960s and are also available on a monthly basis. An advantage of having a large data sample is a reduction in the chance of small sample bias.

Chapter 3: Theory

Research Question:

Does information contained in leading macroeconomic indicators contradict the semi-strong efficient market hypothesis?

Main economic theories:

The main economic theories behind our research question are presented in the book "Investments and Portfolio Management" (Bodie, Kane, Marcus, 2014). Chapter 17 "Macroeconomic and Industry Analysis" treats the broad-based aspects of fundamental analysis – macroeconomic and industry analysis. Chapter 11 "The Efficient Market Hypothesis" presents the theory behind the efficient market hypothesis (EMH).

Efficient Market Hypothesis:

It is common to distinguish among three versions of EMH: the weak, semistrong, and strong forms of the hypothesis. These versions differ by their notions of what is meant by the term “all available information.” (Bodie, Kane, Marcus, 2014).

The weak-form hypothesis asserts that stock prices already reflect all information that can be derived by examining market trading data such as the history of past prices, trading volume, or short interest. This version of the hypothesis implies that trend analysis is fruitless. Past stock price data are publicly available and virtually costless to obtain. The weak-form hypothesis holds that if such data ever conveyed reliable signals about future performance, all investors already would have learned to exploit the signals. Ultimately, the signals lose their value as they become widely known because a buy signal, for instance, would result in an immediate price increase (Bodie, Kane, Marcus, 2014).

The semistrong-form hypothesis states that all publicly available information regarding the prospects of a firm must be reflected already in the stock price. Such information includes, in addition to past prices, fundamental data on the firm’s product line, quality of management, balance sheet composition, patents held, earnings forecasts, and accounting practices. Again, if investors have access to such information from publicly available sources, one would expect it to be reflected in stock prices (Bodie, Kane, Marcus, 2014)

Finally, the strong-form version of the efficient market hypothesis states that stock prices reflect all information relevant to the firm, even including information available only to company insiders (Bodie, Kane, Marcus, 2014).

Macroeconomic and Industry Analysis:

A top-down analysis of a firm’s prospects must start with the global economy. The international economy might affect a firm’s exports prospects, the price competition it faces from competitors, or the profits it makes on investments abroad. It is far harder for businesses to succeed in a contracting economy than in an expanding one. This observation highlights the role of big picture macroeconomic analysis as a fundamental part of the investment process (Bodie, Kane, Marcus, 2014).

The macroeconomy is the environment in which all firms operate. The importance of the macroeconomy in determining investment performance is illustrated in Appendix 1, which compares the level of the S&P 500 stock price index to forecasts of earnings per share of the S&P 500 companies. The graph shows that stock prices tend to rise along with earnings. Thus, the first step in forecasting the performance of the broad market is to assess the status of the economy as a whole (Bodie, Kane, Marcus, 2014).

Business Cycles:

The economy recurrently experiences periods of expansion and contraction, although the length and depth of those cycles can be irregular. This recurring pattern of recession and recovery is called the business cycle. Appendix 2 presents graphs of several measures of production and output. The production series all show clear variation around a generally rising trend. (Bodie, Kane, Marcus, 2014).

The transition points across cycles are called peaks and troughs, indicated by the left and right edges of the shaded regions in Appendix 2. A peak is the transition from the end of an expansion to the start of a contraction. A trough occurs at the bottom of a recession just as the economy enters a recovery. The shaded areas in Appendix 2 therefore all represent periods of recession. When perceptions about the health of the economy become more optimistic, for example, the prices of most stocks will increase as forecasts of profitability rise. Unfortunately, it is not so easy to determine when the economy is passing through a peak or a trough. As we know from our discussion of efficient markets, however, attractive investment choices will rarely be obvious. It usually is not apparent that a recession or expansion has started or ended until several months after the fact. With hindsight, the transitions from expansion to recession and back might be apparent, but it is often quite difficult to say whether the economy is heating up or slowing down at any moment (Bodie, Kane, Marcus, 2014).

Economic Indicators:

Given the cyclical nature of the business cycle, it is not surprising that to some extent the cycle can be predicted. A set of cyclical indicators computed by the Conference Board helps forecast, measure, and interpret short-term fluctuations in economic activity. Leading economic indicators are those economic series that tend to rise or fall in advance of the rest of the economy. Coincident and lagging indicators, as their names suggest, move in tandem with or somewhat after the broad economy. Appendix 3 shows an overview of ten series that are grouped into a widely followed composite index of leading economic indicators. Similarly, four coincident and seven lagging indicators form separate indexes. The composition of these indexes appears in Appendix 4. The dates at the top of the chart correspond to turning points between expansions and contractions. While the index of leading indicators consistently turns before the rest of the economy, its lead time is somewhat erratic. Moreover, the lead time for peaks is consistantly longer than that for troughs (Bodie, Kane, Marcus, 2014).

The relevance, motivation and importance of our research question:

The stock market price index is a leading indicator. This is as it should be, as stock prices are forward-looking predictors of future profitability. However, according to Bodie, Kane, Marcus (2014) this makes leading economic indicators much less useful for investment policy—by the time the series predicts an upturn, the market has already made its move. Although the business cycle may be somewhat predictable, the stock market may not be. This is just one more manifestation of the efficient markets hypothesis (Bodie, Kane, Marcus, 2014).

The main motivation behind our thesis is to present a different set of leading economic indicators compared to those presented by the Conference Board (Appendix 4), Lamont (2000) and Li, Wang, Yu (2017), that can be used to predict both the business cycle and the stock market itself, and thus the contradict the semi-strong efficient market hypothesis. As mentioned in Chapter 2: "Knowledge gap", the focus will be on a specific set of leading economic indicators that that form expectations about economic attributes within specific sectors, that on an aggregate level cover a significant part of the U.S GDP. A detailed description of the data intended for this paper will follow in Chapter 5.

Hypothesis to be tested:

Our hypothesis is that the semi-strong market efficiency hypothesis holds for the S&P 500 Composite Index and thus data contained in leading macroeconomic indicators should not have any predictable forecasting power on stock market returns. With the specific set of leading macroeconomic indicators we intend to focus on the aim of our research is to test whether this hypothesis holds.

Chapter 4: Methodology

Like mentioned in Chapter 2 our research methodology will be based on regression analysis. Regression analysis is primarily aimed at describing and evaluating the relationship between a given dependent variable and one or more other independent variables. OLS is the most common method used to fit a line to the data (Brooks, 2014). In our case, the dependent variable will be monthly returns of the S&P 500 Composite Index, and the main independent variable will be the ISM Manufacturing ROB. In addition, we have three control variables, the University of Michigan Consumer Sentiment Survey, the U.S Census Bureau Building Permits Survey, and the ISM Non-Manufacturing ROB, in order to test whether the explanatory power of the ISM Manufacturing ROB remains significant after controlling for other variables.

We intend to run several types of regression and test different combinations using univariate, bivariate and multivariate regressions. In the univariate case the dependent variable, denoted Y_t, depends on only one explanatory variable, denoted X_{1t}. The relationship between the dependent and independent variable can be expressed the following way:

$$Y_t = \beta_1 + \beta_2 X_{1t} + u_t$$

Where the subscript *t* (=1, 2, 3, …) denotes the observation number, β_1 is a constant and u_t is the residual term that captures all outside random influences on Y_t which cannot be modelled (Brooks, 2014). By adding regressors, we can build bivariate and multivariate regressions, by generalizing the simple model to one with k-1 regressors:

$$Y_t = \beta_1 + \beta_2 X_{2t} + \beta_3 X_{3t} + \ldots + \beta_k X_{kt}\ ,\ t = 1,\ldots,T$$

Each coefficient is now known as a partial regression coefficient, interpreted as representing the partial effect of the given explanatory variable on the explained variable, after holding constant, or eliminating the effect of, all other explanatory variables. (Brooks, 2014).

In order to test various hypotheses and perform statistical inferences on our explanatory variables we intend to run several tests of significance. An important part of using OLS is to make sure that the five underlying assumptions behind classical liner regression models (CLRM) hold:

1) Assumption 1: $E(u_t) = 0$
2) Assumption 2: $Var(u_t) = \sigma^2 < \infty$
3) Assumption 3: $Cov(u_i,u_j) = 0$ for $i \neq j$
4) $Cov(u_t, x_t) = 0$
5) $u_t \sim N(0, \sigma^2)$

The first assumption is that the average value of the errors is zero. In fact, if a constant term is included in the regression equation, this assumption will never be violated. The second assumption is that the variance of the error terms is constant and finite. The third assumption assumes, that the errors are uncorrelated. The fourth assumption is that the *xt* are non-stochastic. The fifth assumption is that the disturbances are normally distributed (Brooks, 2014).

An important part of running statistical inferences is to consider the various assumptions behind the classical linear regression model (CLRM). For instance, in order to test hypotheses, assumption 5 of the CLRM must be hold, namely that $u_t \sim N(0, \sigma^2)$ – i.e. that the error term is normally distributed. (Brooks, 2014).

We intend to use the t-test to test single hypotheses, i.e., hypotheses involving only one coefficient. In order to test for joint significance involving more than once coefficient simultaneously we intend to use the F-test. The F-test involves estimating 2 regressions: The unrestricted regression is the one in which the coefficients are freely determined by the data. The restricted regression is the one in which the coefficients are restricted, i.e. the restrictions are imposed on some βs (Brooks, 2014).
In addition, we need to choose a “significance level”, often denoted α. This is also sometimes called the size of the test and it determines the region where we will reject the null hypotheses that we are resting (Brooks, 2014).

In case we find statistical/economic significant results for the ISM's predictive power for future stock market returns, we will run several robustness checks to address the return predictability, with regards to its connection to for instance; investors' behavioral bias, time-varying risk premium, or other factors of relevance, such as economic growth and economic uncertainty. In addition, we intend to run subsample tests, where we for instance split the full sample period in half, to see if we find similar results in the subsamples. Furthermore, to minimize the potential effect of autocorrelation of errors on the statistical inferences due to potential overlapping data in our sample, we repeat the regression analysis using non-overlapping data. To address the potential issue of small sample bias when the explanatory variables are persistent and the innovations in the explanatory variables are highly correlated with explained variable, we intend to implement a similar approach as Li, Wang, Yu (2017) and run Monte Carlo simulations to investigate whether the statistical inference based on the in-sample t-statistics is affect by size distortions.

Chapter 5: Data

ISM Manufacturing ROB:

Our main predictive variable is the Institute For Supply Management (ISM) Manufacturing Report On Business (ROB). The ISM Manufacturing ROB is a monthly survey based on data compiled from purchasing and supply executives nationwide in the U.S. Membership of the Manufacturing Business Survey Committee is diversified by the North American Industry Classification System (NAICS) based on each industry's contribution to GDP. Manufacturing Business Survey Committee responses are divided into the following NAICS code categories: Food, Beverage & Tobacco Products; Textile Mills; Apparel, Leather & Allied Products; Wood Products; Paper Products; Printing & Related Support Activities; Petroleum & Coal Products; Chemical Products; Plastics & Rubber Products; Nonmetallic Mineral Products; Primary Metals; Fabricated Metal Products; Machinery; Computer & Electronic Products; Electrical Equipment, Appliances & Components; Transportation Equipment; Furniture & Related Products; and Miscellaneous Manufacturing ("ISM-ISM Report – December 2017 Manufacturing ISM® Report On Business®," n.d.).

Survey responses reflect the change, if any, in the current month compared to the previous month. For each of the indicators measured (New Orders, Backlog of Orders, New Export Orders, Imports, Production, Supplier Deliveries, Inventories, Customers' Inventories, Employment and Prices), this report shows the percentage reporting each response, the net difference between the number of responses in the positive economic direction (higher, better and slower for Supplier Deliveries) and the negative economic direction (lower, worse and faster for Supplier Deliveries), and the diffusion index. Responses are raw data and are never changed. The diffusion index includes the percent of positive responses plus one-half of those responding the same (considered positive) ("ISM-ISM Report – December 2017 Manufacturing ISM® Report On Business®," n.d.).

The resulting single index number for those meeting the criteria for seasonal adjustments (PMI®, New Orders, Production, Employment and Supplier Deliveries) is then seasonally adjusted to allow for the effects of repetitive intra-year variations resulting primarily from normal differences in weather conditions, various institutional arrangements, and differences attributable to non-moveable holidays. All seasonal adjustment factors are subject annually to relatively minor changes when conditions warrant them. The PMI® is a composite index based on the diffusion indexes of five of the indexes with equal weights: New Orders (seasonally adjusted), Production (seasonally adjusted), Employment (seasonally adjusted), Supplier Deliveries (seasonally adjusted), and Inventories. ("ISM-ISM Report – December 2017 Manufacturing ISM® Report On Business®," n.d.)

The ISM Manufacturing ROB survey is sent out to Manufacturing Business Survey Committee respondents the first part of each month. Respondents are asked to only report on information for the current month. ISM receives survey responses throughout most of any given month, with the majority of respondents generally waiting until late in the month to submit responses in order to give the most accurate picture of current business activity. ISM then compiles the report for release on the first business day of the following month ("ISM-ISM Report – December 2017 Manufacturing ISM® Report On Business®," n.d.).

The ISM Non-Manufacturing ROB:

The ISM Non-Manufacturing ROB is based on the exact same features as the ISM Manufacturing ROB. However, the Non-Manufacturing Business Survey Committee responses are divided into the following NAICS code categories:

Agriculture, Forestry, Fishing & Hunting; Mining; Utilities; Construction; Wholesale Trade; Retail Trade; Transportation & Warehousing; Information; Finance & Insurance; Real Estate, Rental & Leasing; Professional, Scientific & Technical Services; Management of Companies & Support Services; Educational Services; Health Care & Social Assistance; Arts, Entertainment & Recreation; Accommodation & Food Services; Public Administration; and Other Services (services such as Equipment & Machinery Repairing; Promoting or Administering Religious Activities; Grantmaking; Advocacy; and Providing Dry-Cleaning & Laundry Services, Personal Care Services, Death Care Services, Pet Care Services, Photofinishing Services, Temporary Parking Services, and Dating Services) ("ISM-ISM Report – December 2017 Non-Manufacturing ISM® Report On Business®," n.d.).

The University of Michigan Survey of Consumer Sentiment:

The Surveys of Consumers are conducted by the Survey Research Center, under the direction of Richard T. Curtin, at the University of Michigan. The core questions cover three broad areas of consumer sentiment: personal finances, business conditions, and buying conditions ("Surveys of Consumers, "n.d.).

United States Census Bureau Building Permits Survey:

The Building Permits survey is a monthly survey of 9,000 selected permit-issuing places. The purpose of the Building Permits Survey is to provide national, state, and local statistics on new privately-owned residential construction. The statistics from the Building Permits Survey are based on reports that are submitted by local building permit officials in response to a voluntary mail survey (US Census Bureau (MCD): Cornish, Cooper, Jenkins, n.d.).

Summary Statistics:

Summary Statistics

	ISM Manufacuting ROB	ISM Non-Manufacuting ROB	Survey of Consumers	U.S. Census Bureau Building Permits
Mean	52,82	53,68	86,23	1356,05
Median	53,30	54,80	89,65	1328,00
Std	7,35	4,29	12,37	391,81
Kurtosis	0,72	2,75	-0,41	-0,33
Skewness	-0,29	-1,55	-0,48	0,16
Minimum	29,40	37,60	51,70	513,00
Maximum	77,50	60,30	112,00	2419,00

Correlation matrix

	ISM Manufacuting ROB	ISM Non-Manufacuting ROB	Survey of Consumers	U.S. Census Bureau Building Permits
ISM Manufacuting ROB	1			
ISM Non-Manufacuting ROB	0,77	1		
Survey of Consumers	0,4	0,67	1	
U.S. Census Bureau Building Permits	0,19	0,51	0,81	1

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Appendix:

Appendix 1: S&P 500 Index versus earnings per share

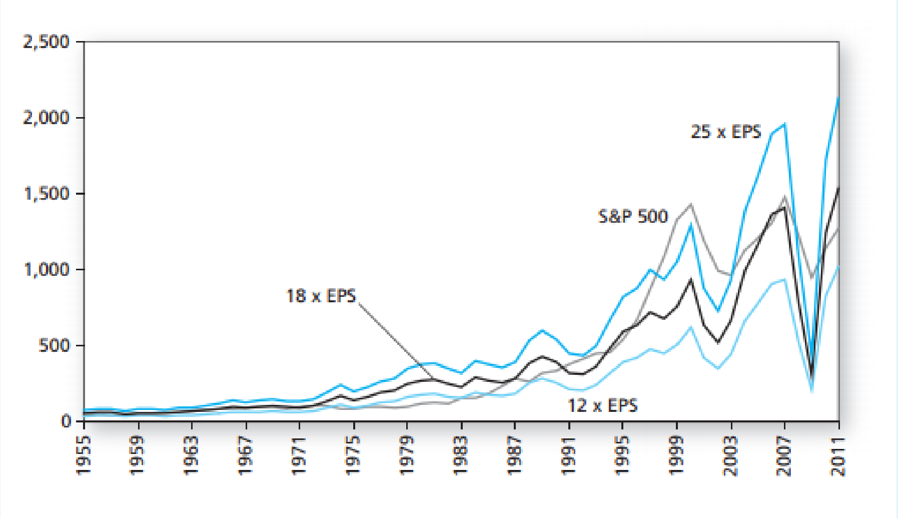

Figure 17.2 S&P 500 Index versus earnings per share

Source: Authors' calculations using data from *The Economic Report of the President*.

Appendix 2: Cyclical Indicators

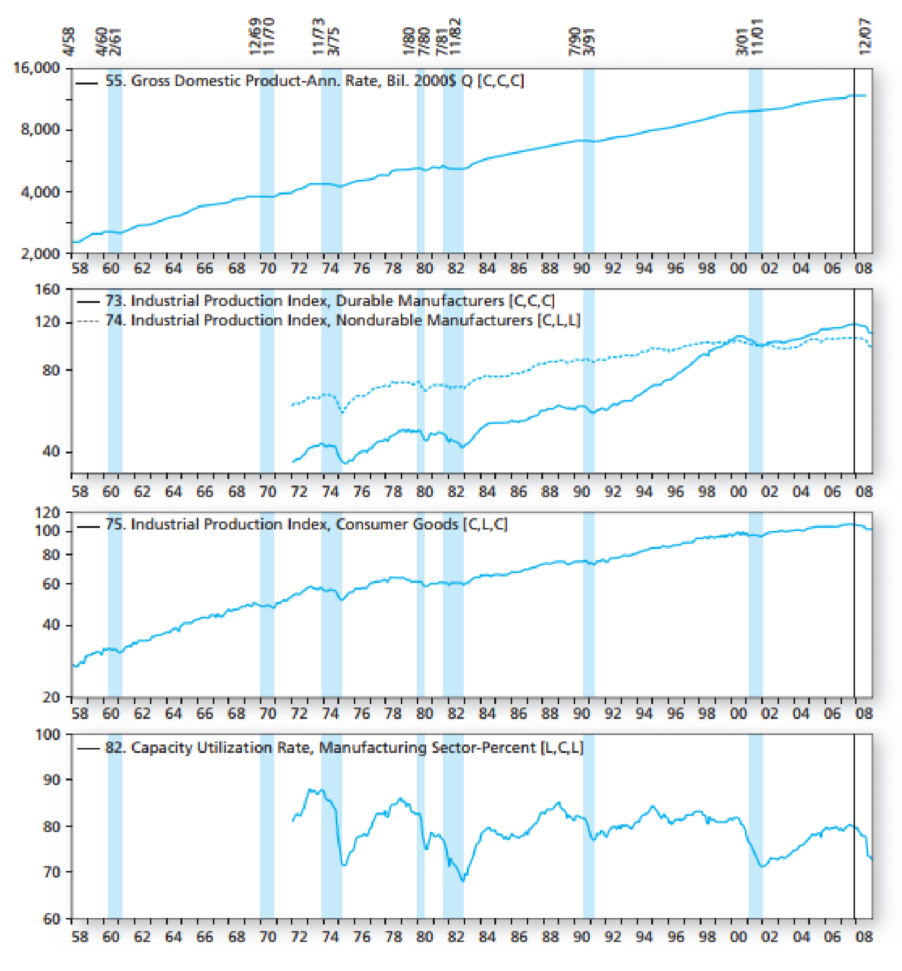

Figure 17.3 Cyclical indicators

Source: The Conference Board, *Business Cycle Indicators*, December 2008. Used with permission.

Appendix 3: Economic indicators

Table 17.2

Indexes of economic indicators

A.	**Leading indicators**
1.	Average weekly hours of production workers (manufacturing)
2.	Initial claims for unemployment insurance
3.	Manufacturers' new orders (consumer goods and materials industries)
4.	Fraction of companies reporting slower deliveries
5.	New orders for nondefense capital goods
6.	New private housing units authorized by local building permits
7.	Yield curve slope: 10-year Treasury minus federal funds rate
8.	Stock prices, 500 common stocks
9.	Money supply (M2) growth rate
10.	Index of consumer expectations
B.	**Coincident indicators**
1.	Employees on nonagricultural payrolls
2.	Personal income less transfer payments
3.	Industrial production
4.	Manufacturing and trade sales
C.	**Lagging indicators**
1.	Average duration of unemployment
2.	Ratio of trade inventories to sales
3.	Change in index of labor cost per unit of output
4.	Average prime rate charged by banks
5.	Commercial and industrial loans outstanding
6.	Ratio of consumer installment credit outstanding to personal income
7.	Change in consumer price index for services

Source: The Conference Board, *Business Cycle Indicators*, November 2012.

Appendix 4: Indexes of leading, coincident, and lagging indicators

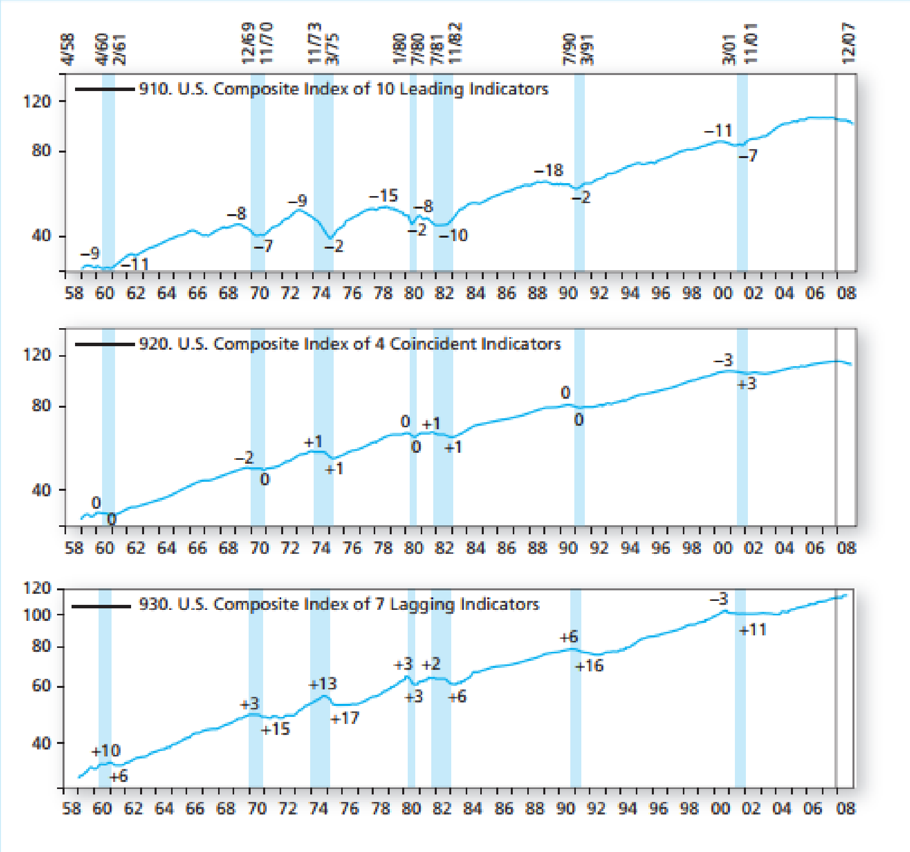

Figure 17.4 Indexes of leading, coincident, and lagging indicators

Note: Shaded areas represent recessions.

Source: The Conference Board, *Business Cycle Indicators*, December 2008. Used with permission.