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Covid-19, Indicators, and the Stock Market

- An Assessment of Indicators' performance in relation to the Stock Market during Covid-19

Master's Thesis in Information Systems
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Abstract:

Market participants can use economic and financial indicators to predict and follow changes in the stock market. However, Covid-19 has caused uncertainty in the economy and financial markets since its spread. Additionally, the U.S. economy entered a recession in February 2020, and the stock market crashed in March 2020. During volatile times, reliable indicators are necessary for assisting market participants' decision-making. Therefore, it is important to assess the indicators' performance. Previous studies have provided information on indicators that are of reliable use. However, the findings from previous studies vary, depending on the characteristics of the economic situation.

The main aim of this study was to determine how indicators have been affected by Covid-19 and how well they have performed in relation to the stock market. Another aim was to assess if the indicators display information, that is, leading, coincident, or lagging in relation to the stock market indices. Furthermore, similar indicators were compared, and factors affecting the indicators during Covid-19 were described.

For the purpose of this study, nine indicators and two stock market indices were included. The indicators were assigned into the categories: macroeconomic, survey-based, and business cycle. Their performance was analyzed in relation to the development of the U.S. stock market indices S&P 500 index and DJIA. Monthly data with the time period of January 2019 to January 2020 were analyzed. Statistical analyzes, such as correlation, correlation significances, cross-correlation, simple linear regression, and multiple linear regression, were performed to assess the indicators and their relationship with the stock indices.

The results showed that the stock market indices were leading the indicators. Hence, the results imply that indicators could not be reliably used in forecasting the development of the stock indices during the period from January 2019 to January 2021. Furthermore, the indicators were also affected directly and indirectly by regulations and lockdowns the U.S. government ordered to combat Covid-19.

Keywords: stock market, Covid-19, economic indicators, stock market crash, macroeconomic indicators, survey-based indicators, business cycle, recession

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Abbreviations

PMI - Purchasing Managers' Index

CLI - Composite Leading Indicator

CPI - Consumer Price Index

PPI - Producer Price Index

CSI - Consumer Sentiment Index

S&P 500 index - Standard and Poors' 500 index

DJIA - Dow Jones Industrial Average

APT - Asset pricing theory

CAPM - Capital asset pricing model

ISM - Institute for Supply Managers

BLS - Bureau of Labor Statistics

NBER - National Bureau of Economic Research

1 Introduction

The Covid-19 pandemic has caused economic instability in financial markets. The pandemic is responsible for increasing uncertainty in stock market prices due to changes in price volatility. The most noticeable repercussion that materialized at the beginning of 2020 was the stock market crash in March (Mazur et al., 2021). The sudden nature of the pandemic, as well as the regulations governments have implemented to combat it, further exacerbated the uncertainty on the stock market.

The National Bureau of Economic Research (NBER) declared that the most recent peak in the U.S. business cycle occurred in February 2020, meaning that the U.S. economy entered a recession (NBER, n.d.). Research indicates that the stock market and the state of the business cycle are connected (Perez-Quiros &Timmermann, 2007; Naes et al., 2011; Franz, 2010). In general, an expanding business cycle leads to an increase in stock market prices. In contrast, a contracting business cycle leads to a decrease in stock market prices. Additionally, stock market fluctuations can anticipate the state of the business cycle (Franz, 2010). That is, a rise in stock market prices can anticipate an expansion of the business cycle, and a fall in the stock market prices can anticipate a contraction of the business cycle. In other words, the stock market prices fluctuate and mimic the movement of the business cycle, and the business cycle, in turn, can be anticipated by the fluctuations of the stock market. The abovementioned fluctuations in the stock market are called bull (i.e., an increase in prices) and bear (i.e., a decrease in prices) markets.

The state of the business cycle can be examined by observing different economic indicators. When predicting business cycle turning points, organizations and investors use leading economic indicators that show in advance how the business cycle will turn. The use of economic indicators in relation to the business cycle is usually focused on observing economic development from a macroeconomic perspective, concentrating on a country's gross domestic product (GDP) (Zarnowitz, 1991).

Participants in the stock market attempt to use all the available information in anticipating the fluctuations of the stock market. As with examining the business

cycle, economic and financial indicators in relation to the stock market can be used. The indicators provide information that shows past, current, and future fluctuations of the stock market. The uncertainty that the Covid-19 pandemic has caused to the stock market has further raised the importance of accurate indicators. Especially the indicators' predictive abilities and how they should be interpreted have come into question.

Due to the unexpected nature of the Covid-19 pandemic and the ongoing uncertainty it has led to, market participants in the stock market need to find alternative ways to gain the correct information as to how to participate in the stock market. Indicators have been used for the purpose of gaining insight into how the stock market develops. In this thesis, macroeconomic indicators, survey-based indicators, and business cycle indicators are grouped under the term indicators.

1.1 Background

Indicators are used to gain more information about the stock market and business cycles in general. Hence, the reliability of the indicators and how they can be used are important for market participants and decision-makers. Among the earliest research in using indicators in an attempt to predict the business cycle is that done by Mitchell and Burns (1946;1961). The authors argued that by observing indicators that are constructed in different ways and measure different economic activity, one would obtain a clearer and broader picture of the business cycle. This, in turn, could help in forecasting recessions and increased economic activity. Further, individual indicators have performed non-consistently during different recessions (Stock & Watson, 2003). Stock and Watson (2003) observed how indicators performed during the 2001 recession and concluded that the performance of the indicators was different from previous recessions. For instance, consumer confidence and building permits decreased, both before and during the 1990 recession, but they did not decrease before the 2001 recession. Stock and Watson (2003) argued that the reasons for this could be that the U.S. economy has made fundamental changes. Where international trade has increased, financial markets have developed, and the increase of technology in industries has made the underlying conditions different. Similar to

the 2001 recession, the decline in the stock market prices at the beginning of 2020 was a forecaster of the recession.

NBER, which announces the dates of the US business cycles' turning points, declared that the most recent peak occurred in February 2020 (NBER, n.d.). The recession, with an onset in 2020, has continued into 2021, started with the stock market crash in March 2020. The stock market crash was soon stabilized, but the actions that different authorities put into place, mainly quarantines and regulations for business activity to lessen the burden of the virus, led to outcomes that affected employment and spending. The virus has further affected economic activity, most notably in the tourism industry and later many other industries, through the downturn in consumer activity (Congressional Budget Office Reports, 2020).

Schoenfield (2020) studied how the Covid-19 pandemic affected the financial markets by examining the S&P 500 companies. He observed how individual firms and industries were affected. According to him, the pandemic led to approximately 95% of the S&P 500 companies decreasing in value during the three first months of 2020, however, mainly during the crash of March. According to Schoenfield (2020), the most affected firms were those in the following areas: energy, clothing, restaurants and hotels, transportation, cars, machinery, and railroads. On a more general note, Schoenfield (2020) observed that the pandemic influences the financial markets, including changes in unemployment, the value of bonds, commodities, and currencies. Concerning the S&P 500 companies, most decreased in value.

The effects of the stock market crash and the implications of how the pandemic continues to affect the economy and economic development have not yet been fully comprehended. This underlines the need for the present thesis.

1.2 Problem Discussion

Previous research shows mixed results in how different indicators have performed. Varying results are dependent on indicators' performance during different stages of the business cycle. Additionally, the same can be observed when measuring indicators' performance in relation to stock market development. The attempt to gain

a broader and more consistent view of economic development led to the construction of composite indicators (OECD, 2021). Composite indicators attempt to construct a clearer picture of economic development by combining variables representing different economic aspects. Nevertheless, the consensus is that using many indicators measuring different aspects of economic development provides the most precise picture. Hence, I decided to include numerous indicators in my study.

The stock market crash in March 2020 was a rapid external shock, affecting the valuation of stock market prices and eventually leading to a fast but somewhat short-lived stock market crash. The stock market crash occurred during the beginning of the recession, with heavy price fluctuations. Previous research has examined how indicators have functioned before recessions and how they have perceived stock market crashes, but the results concerning this are mixed (Stock & Watson, 2003). How well indicators have measured economic development before and after stock market crashes also depends on the studied indicators.

A more globalized economy might have contributed to the uncertainty in how well the indicators measure economic and stock market development. Most of the companies listed on significant stock market indices act in many different economies and economic spheres. This is causing some parts of the companies' economic activities not to be perceived by indicators measuring only the U.S. economy. The possibility of being affected by economic shocks outside the U.S. economic sphere can influence the stock market price of the affected company listed on the U.S. economic indices.

The indicators' performance in relation to the stock market during Covid-19 may have also been affected by factors related to government regulations made to combat the pandemic. For instance, business regulations may have affected indicators' performance in managing reliably to measure economic activity in relation to the stock market. This could have further increased the uncertainty of the indicators' performance during Covid-19.

The stock market in relation to indicators has usually been studied by concentrating on either stock market returns or stock market prices. The prices and returns have represented the stock market in these studies. Additionally, how the indicators can explain and predict stock market development has considered how the indicators can

be used in relation to stock market prices or returns. This study will include previous literature from both of the former and the latter viewpoints to gain a comprehensive picture of the relationship between the indicators and the stock market.

1.3 Aims

The main aim of this study was to research how the selected indicators can explain the variation of the stock market indices' values and how they have been affected by the Covid-19 pandemic. For this purpose, nine indicators and two stock market indexes were included in the present study. Further, the second aim was to observe if the indicators display information, that is, leading, coincident, or lagging in relation to the stock market indices. The third aim of the study was to determine whether the use of a single indicator or multiple indicators better explains the development of the stock market indices. Further, observe how the indicators have performed compared to other similar indicators. An additional aim was to ascertain how the indicators could be used in forecasting the stock market indices. Lastly, how well and accurately can the indicators measuring monthly data be used in achieving the aims of the study. All the included indicators measure the development of the U.S. economy.

Due to previous research has not come to a consensus on the relationship between the stock market and the indicators, no hypotheses were constructed in the present study. Instead, research aims were formed, which explain what the present study is attempting to achieve.

1.4 Methodology

The author of this study wanted to know how the indicators have been affected by the external shock that the Covid-19 pandemic caused the stock market. Therefore, the indicators were tested as to whether they have been functioning properly and giving a correct picture. In other words, the indicators' reliability and measurements were analyzed. Conducting these analyses is of practical value, as the findings could be used by decision-makers and private participants in the stock market.

To be able to determine how the indicators had measured economic activity in relation to the stock market both before and during the Covid-19 pandemic, data from the years 2019-2021 were included. The data from the time period before the onset of the pandemic were compared against the data gathered during the pandemic to understand the differences in the indicators' measurements.

The indicators have been assigned into three categories, determined by the economic activity they measure and how they measure it. The categories are the following: Survey-based indicators; that include the Purchasing Managers' indices (PMI) and the Consumer Sentiment Index (CSI), Macroeconomic indicators; that includes the Industrial Production Index (IPI), Producer Price Index (PPI), and the Consumer Price Index (CPI), and to the Business cycle, that includes the OECD Composite Leading Indicator (CLI).

To examine whether the indicators have a positive relationship with the stock indices, correlations and cross-correlations were performed. Further, correlations and correlation significances among indicators were performed. Additionally, various regression analyses were conducted to observe if there were linear relationships with the indicators and stock indices. Firstly, simple linear regression analyses of the stock market indices against each indicator were performed. Secondly, simple linear regressions with lagged values for the indicators were conducted. Thirdly, multiple regression analyses were performed with the indicators that showed the lowest correlations and lowest correlation significance values. Finally, multiple regression analyses with lagged values for the indicators were conducted.

1.5 Delimitations

This study focuses on how indicators can measure stock market development and on the indicators' predictive abilities in relation to the stock market. For this reason, nine indicators and two stock market indices were included. The two stock market indices, the S&P 500 index and the DJIA, were chosen for the vast number of listed companies on the indices. The S&P 500 index was included since the 500 largest publicly traded companies are included in the index (Standard & Poors' 500 index factsheet, n.d.). The DJIA was included due to the listed companies are of the 30

largest in the U.S (Dow Jones Industrial Average factsheet, n.d.). The nine indicators were chosen based on widespread use by market participants and an extensive amount of previous research.

Previous research focuses primarily on how indicators have measured the development of the U.S. economy and stock markets, but research that encompasses other countries' stock markets was also included in the current study. Many of these countries have developed economies and stock markets that have similarities with the U.S. stock market. Furthermore, the timeframe for the data in the study was from January 2019 to January 2021.

1.6 Structure of the Study

The study is divided into six sections. The first section includes the introduction and background to the topic, the description of the problem, the delimitations of the study, and the aims of the study. The second section contains the theoretical foundation of the study and literature on how the indicators have performed in earlier studies. The third section contains the methodology of the present study. Different analytical methods are explained, and how the analyses are conducted will be discussed. The fourth section contains the results of the analysis. The results of the study will be presented and concurrently shortly discussed. In the fifth section, the results are further discussed and compared to the findings of previous literature. The discussion is divided according to the categories of the indicators. Limitations of the current research are also presented. In the sixth section, concluding remarks and suggestions for future research are made.

Table 1 Indicators

Category	*View*	*Indicator*
Survey-based	Manufacturing (Business Cycle)	ISM Manufacturing PMI
	Service (Business Cycle)	ISM Non-Manufacturing PMI
	Manufacturing and Service (Business Cycle)	Chicago PMI
	Manufacturing (Business Cycle)	IHS Markit PMI
	Sentiment (Consumption)	The University of Michigan's consumer sentiment index
Macroeconomic	Inflation (Consumption)	Consumer Price Index
	Inflation (Production)	Producer Price Index
	Production	Industrial Production Index
Business Cycle	Business Cycle	OECD CLI

2 Theories and Literature Review

The objective of this section is to present the theories of the topics relevant to this study. That is the presentation of how and why the business cycle fluctuates, its connection to the stock market, and theories related to what determines the development and the returns of the stock market. Later, the indicators and results from earlier studies will be presented.

The theories, directly and indirectly, relate to how the indicators function and how they can be used in understanding the stock market. Some indicators, such as business cycle indicators, are more directly based on theories related to how the business cycle fluctuates. However, the fluctuations of the business cycle and the fluctuations of the stock market share commonalities, creating the possibility of using the indicators in relation to the stock market. Indicators, such as macroeconomic indicators, are explained as factors affecting the stock market, being a part of stock market pricing theories attempting to explain the variation of stock market development and returns. The indicators, the methods they are constructed and how they measure economic activity, and, in turn, how the economic activity affects the stock market, are varying. Therefore, to understand the context of the present study and the indicators, relevant theoretical concepts are presented.

The first part of this section can be described as an introduction, presenting the theoretical foundation of how the stock market and business cycle functions and the indicators' use in relation to them. The latter part, in turn, can be described as a literature review, in which the indicators included in the study are presented and results how they have been researched in relation to the stock market are described.

This section begins with a short introduction to business cycles, followed by the presentation of linkages between the stock market and business cycles. Furthermore, the stock market and theories related to it are described to understand what factors influence the development of the stock market. The section ends with the presentation of the indicators included in the present study and how they have performed in previous studies in relation to the stock market.

2.1 A Short Introduction to Business Cycles

Business cycles show the aggregate movement of economic activity. The economic activity can be classified into different turning points, peaks, and troughs, which show the highest and lowest points of the economy (Zarnowitz, 1991). A business cycle is characterized by recessions and expansions, which occur between the peaks and troughs. Hence, the expansions and recessions lead to each respective turning point of the business cycle. Recessions are periods when economic activity declines for a more extended period, whereas expansions are the contrary (Zarnowitz, 1991).

The movement of the business cycle is a difference between the actual GDP and the potential GDP (Eklund, 2013). When the actual GDP is above the potential GDP, the economy is in an expansion. When the actual GDP is below the potential GDP, the economy is in a recession (Eklund, 2013). Reasons for recessions could be caused by external disruptions and negative outlooks for the future, and the Covid-19 pandemic has fulfilled both abovementioned claims.

Some indicators attempt to predict the fluctuations of the business cycle. These indicators are more commonly referred to as business cycle indicators. A well-known business cycle indicator is the OECD Composite Leading Indicator (CLI).

2.1.1 The Stock Market and the Business Cycle

Research has demonstrated a connection between the stock market and business cycles. A part of the current study has concentrated on analyzing the connection between the stock market and the turning points of the business cycle.

A general notion is that when the economic activity increases, the stock market prices increase due to increased economic output. When economic activity decreases, the stock market prices decrease. The linkages between the stock market and the business cycle have been observed from different viewpoints, through volatility, by Perez-Quiros and Timmermann (2007), Raunig and Scharler (2010), and Hamilton (1996), to name a few. Researchers observing volatility as the source of the connection between the stock market and business cycles deem that a higher level of

volatility leads to a higher level of uncertainty regarding the economic activity. Higher levels of uncertainty, in turn, lower consumption and investing, which causes the business cycle to turn, and the economy affected.

A second researched link between the stock market and the business cycle is stock market liquidity. The decline of liquidity in the stock market decreases the number of participants in the stock market. Additionally, stock market liquidity has shown to decrease before the business cycle has started a turning point for recessions (Naes et al., 2010).

The stock market has even been shown to be used to predict business cycles (Franz, 2010). The stock index, S&P 500 index, used in Franz's (2010) study could be applied in forecasting business cycle turning points. Estrella's and Mishkin's (1998) findings are in line with Franz's (2010) findings. They studied how financial indicators can be used in the prediction of U.S. recessions. One of the variables that they included in their study was stock market prices. The results from the study conducted by Estrella and Mishkin (1998) indicated that the stock market prices can function as a leading indicator in the prediction of recessions by one to three quarters. The connections between the stock market and business cycles can illustrate why they often fluctuate in tandem and why a stock market crash often precedes a recession.

2.2 Stock Market Theories and Asset Pricing Models

Stock market theories attempt to state what determines the stock market prices and returns. The efficient market hypothesis and random walk hypothesis, which explain how the prices and returns can be determined through how the markets and the assets themselves function, are presented. In addition, theories that explain what factors affect the stock market returns through asset pricing theories, such as the capital asset pricing model and multifactor model of the arbitrage pricing theory, are presented.

2.2.1 The Efficient Market Hypothesis

The efficient market hypothesis states that all the information of the financial assets, including the stocks in the stock market, is reflected in the asset's price. The efficient market includes all the information of the assets, and this information is ready to be used by market participants (Malkiel, 2003).

In an efficient market, the stock market contains all the information that influences the stock price. Further, when the information is incorporated in the stock price, there is no major difference in the stock's actual and intrinsic value (Fama, 1995). This, in turn, means that there are no undervalued stocks in the efficient market theory. All the information is always available for all the market participants, and this information is random, then the stock prices at a random time are only affected by the information available at that time (Malkiel, 2003).

Malkiel (2003) states that the efficient market receives critique by not taking behavioral and psychological aspects of the markets into consideration. For instance, the behavior of some market participants is sometimes irrational, and other market participants can benefit from this. Malkiel (2003) argues that this implies that stock prices and returns partially predictable. The efficient market hypothesis can therefore be said to explain the development of stock market prices partly.

2.2.2 The Random Walk Hypothesis

The random walk hypothesis states the opposite of the efficient market hypothesis, which is that the price of a stock is random (Fama, 1995). The historical values that the stock market has had in the past have no connection with today's value and cannot be used in the prediction of future stock market values (Fama, 1995). In the hypothesis, the actual value for an asset is 'randomly walking' from the intrinsic value.

Fama (1995) argues that the random walk hypothesis can explain the changes in the intrinsic and actual values of an asset. Changes in the intrinsic value cause under- and over-adjustment of the asset's actual value, and it takes time for the changes of

the intrinsic value to be reflected in the actual value. In addition, there is a time lag that is independent of interference for the actual values to adjust to intrinsic values (Fama, 1995). The change in the actual values may occur before the change has occurred in the intrinsic value or afterward, reflecting the random nature of how the values change.

Fama (1995) argues that the random walk hypothesis may not be entirely correct but that there is some truth to the hypothesis. The price movements of the asset may not be fully independent or dependent on historical price movements. The degree to how dependent future price movements are on historical price movements defines the possibility to predict future stock market prices.

2.2.3 The Capital Asset Pricing Model

The relationship between the expected return and risk of a stock is described in the capital asset pricing model (Perold, 2004). The expected return is influenced by the time value of money (the risk-free rate) and the market premium (Perold, 2004). The market premium is the return of the market subtracted by the risk-free rate. How much a market participant is willing to take more risk is represented by a risk measure (beta), which compares the stock returns to the market and market premium.

The model states that diversification of the assets in a portfolio lowers the risk of the portfolio, but there is still a correlation between the risks associated with the assets (Perold, 2004). This means that there still are some levels of risks in the portfolio that cannot be eliminated from the portfolio, which is represented by the beta. Therefore, diversification of the portfolio cannot eliminate all the risks (Perold, 2004). The objective then becomes to choose the level of expected return and risk from the portfolio. The formula for the CAPM is the following:

$$E_s = R_f + \beta_i (E_m - R_f) \tag{2.1}$$

Where:

E_s = *expected return of an asset,*

R_f = *risk-free rate,*

B_i= *beta of the asset,*

E_m= *expected return of the market portfolio,*

$(E_m - R_f)$= *market risk premium*

The model has many variations that consider different economic factors. There is a variation of the CAPM that takes foreign-exchange risk into account (e.g., international CAPM) (Dumas, 1994). CAPM and its extensions can further consider other variables affecting asset prices, such as the state of the business cycle. A model where the beta changes according to the business fluctuations is called the conditional CAPM (Dumas, 1994).

The CAPM and the behavior of stock markets have been attempted to explain by using business cycle indicators (Dumas, 1994). More specifically, economic activity and stock market return. Dumas (1994) tested different capital asset pricing models, such as the international and conditional international CAPMs. He concluded that specific nonfinancial business cycle indicators could help predict stock market returns and explain the behavior of the stock market. Dumas (1994) used the indicators to help in determining if the conditional CAPMs functioned adequately, that is if the indicators could explain the behavior of the stock market through the conditional CAPMs. The author concluded that the international conditional CAPM did function, which proved the relationship between the business cycle indicators and stock market returns.

Two popular variations of the CAPM are the production-based asset pricing model and the consumption-based capital asset model. These models will be shortly presented next.

2.2.3.1 Consumption-based Asset Pricing Model

The consumption-based asset pricing model differs from the CAPM by replacing the market risk with a consumption risk that affects the expected return of assets (Chen, 2003). The risk is associated with how owning an asset increases or decreases the uncertainty in consumption. When a market participant has invested in a risky asset, the market participant's consumption may negatively turn because the market

participant's total wealth may be negatively affected by the risky asset (Chen, 2003). The model has a consumption beta that measures a consumption growth risk (Chen, 2003). According to Cochrane (1991), in the consumption-based asset pricing model, stock market returns and consumer decisions affecting the marginal rates of substitution are connected by a utility function. The utility function is based on the results of the consumers' decisions for an intertemporal consumption demand (Cochrane, 1991).

2.2.3.2 Production-based Asset Pricing Model

Production-based asset pricing models attempt to link asset returns to production variables (Cochrane, 1991). In addition, there is a relationship between returns of the stock market and production-based variables. This relationship can be studied through the production-based asset pricing model. Cochrane (1991) states that variables affecting production are linked to asset returns. In the production-based asset pricing model, the decisions made by companies on their production and investment affect the marginal rates of transformation, which are tied together with asset returns by a production function (Cochrane, 1991). The production function is based on the producer's decisions for intertemporal investment demand (Cochrane, 1991).

2.2.4 Arbitrage Pricing Theory – Multifactor model

The multifactor model of the arbitrage pricing theory connects macroeconomic variables with stock market returns (Priestley, 1996). In the model, stock returns are influenced by economic variables, such as unanticipated changes in risk premiums, changes in the expected level of industrial production, unanticipated inflation, and unanticipated changes in the shape of the interest rates' term structure (Ross, 1976).

In the multifactor model, the asset's return is affected by the asset's expected return and different macroeconomic variables that can increase or decrease the risk of the asset (Priestley, 1996). According to the model, asset prices are not always correctly

priced, leading to opportunities for arbitrage. In the model, one can include multiple macroeconomic variables that affect the risk and return of different assets. Further, macroeconomic variables bring systematic risk and risk premiums (Priestley, 1996). Additionally, the market participants are expected to diversify their portfolios based on risks. The expected return of an asset is a linear function of the risk of the asset relative to factors, such as macroeconomic variables (Ross, 1976). Next, the formula of the multifactor model is presented:

$$R_i = A_f + (B_{i1} * L_1) + (B_{i2} * L_2) + \ldots + B_n * L_n \qquad (2.2)$$

Where:

A_f = risk-free rate of return of the asset,

L_n = risk premium for the factor,

B_n = sensitivity of the asset in relation to a specific factor,

R_i = expected return of the asset

2.3 Indicators

The indicators included in the present study are assigned into three categories: survey-based, macroeconomic, and the business cycle. The indicators differ in the underlying methods, how they are constructed, and by what they measure. The only 'pure' business cycle indicator in this study is the OECD CLI. The PMIs are partly business cycle indicators due to them measuring contractions and expansions in relation to economic sectors. However, they also measure expectations and overall sentiment in these economic sectors. Additionally, they are constructed by surveys and 'soft' data, which is why they are grouped in the survey-based category.

Composite indicators can be used for gaining an understanding of stock market fluctuations. Additionally, depending on what variables they cover, they can be argued to provide a more comprehensive picture of stock market fluctuations than using single economic indicators. Furthermore, composite indicators can eliminate irregularities that single indicators produce (Ficthner et al., 2007)). Composite

indicators can be constructed by many variables such as financial and economic variables or by grouping together different questions, such as it is done by the PMIs.

2.3.1 Macroeconomic indicators

Macroeconomic indicators are used in discovering and determining the stock market fluctuations, price changes, and stock market returns. Chen (2009) observed how macroeconomic variables are used to predict the U.S. bear stock market in the S&P 500 stock market index. The best performing variables that the author used in the prediction of bear markets were the variable yield curve spreads and the variable inflation rates. Chen (2009) also argues that using macroeconomic variables in the prediction of bear markets surpasses the performance of predicting stock returns with macroeconomic variables.

Chen et al. (1986) studied different macroeconomic variables and how they affect expected stock returns in asset pricing. The macroeconomic variables that affected expected stock returns the most were industrial production, changes in the yield curve, and risk premium. Furthermore, during volatile times unexpected inflation and changes in expected inflation were significant in determining expected stock returns (Chen et al., 1986). Furthermore, the variables had a more significant effect on the expected returns than the New York Stock Exchange index.

Rapach et al. (2005) studied how macroeconomic variables can help in predicting stock market returns in 12 different countries. They included macroeconomic variables, such as the inflation rate, money stocks, interest rates, term spreads, industrial production, and unemployment rate. Of all the included macroeconomic variables, the predictive ability of interest rates performed best in all the observed countries. However, the authors concluded that stock returns are difficult to predict since speculation and other factors constitute most stock returns, and the predictable part of stock returns is negligible.

The results of what variables affect the stock market the most are conflicting. Frequently studied variables are, for instance, money supply, industrial production and manufacturing, interest rates, unemployment, and inflation. The results from

previous studies vary depending on the researched country and how developed the country's economy is. Moreover, many macroeconomic variables affect each other, and historical changes in the variables can be used in predicting the current values of the variables (Serfling & Miljkovic, 2011).

Indicators that measure macroeconomic factors present information about the stock market when lagged. Celebi and Hönig (2019) observed how lagged indicators in the German economy present information on the DAX30 stock index development. The study was divided into three periods: a pre-crisis period, a post-crisis period, and a crisis period, where some ECB countries were under economic duress. During the crisis period, the lagged indicators impacted the companies listed on the DAX30 more than they did during the pre-and post-crisis periods (Celebi & Hönig, 2019).

2.3.1.1 The Producer Price Index

The Producer Price Index (PPI) measures price movements in domestic production (BLS, n.d.c). The PPI is published monthly by the Bureau of Labor Statistics (BLS). The PPI has been observed to both affect the stock market returns and to have an effect on how the stock market develops (Flannery & Protopapadakis, 2002; Sirucek, 2012). An increase in the PPI shows an increase in inflation, affecting the level of returns of the market portfolio (Flannery & Protopapadakis, 2002). Sirucek (2012) studied how macroeconomic variables affect the development of the S&P 500 index and the development of the DJIA index. Sirucek (2012) concluded that the PPI had a negative impact on the development of the stock indices. Additionally, the relationship between the development of the DJIA index and the PPI was more significant than the relationship between the PPI and the development of the S&P 500 index.

Macroeconomic news and information influence the stock market, foreign exchange, and the U.S. bond market (Suk Joong et al., 2004). Information and news related to the PPI and the Consumer Price Index (CPI) influence how the U.S. stock market develops (Suk Joong et al., 2004). The authors discovered that a significant positive effect in mean stock market returns emerged when the PPI and CPI were lower than previously expected. In comparison, negative inflation news resulted in minor stock

market returns. In addition, Suk Joong et al. (2004) concluded that the stock market returns are affected predominantly by news related to price levels and inflation, while the stock market, foreign exchange, and the bonds market are affected by information and news explicitly related to the PPI.

2.3.1.2 The Consumer Price Index

The Consumer Price Index (CPI) measures the change in prices of goods and services that are paid by the consumer (BLS, n.d.a). The CPI is published by the BLS monthly. Flannery and Protopapadakis (2002) concluded that the CPI functions as a risk factor to stock market returns. The relationship between the CPI and the stock market is similar to the relationship between the PPI and the stock market. An increase in either the PPI or the CPI shows an increase in inflation, affecting the market portfolios' returns.

Hamid et al. (2006) researched the price transmission between the following variables: CPI, PPI, S&P 500 index, and DJIA. The price transmission varied through three different time periods, 1926-1945, 1946-1972, and 1972-2003. The authors concluded that during the most recent time period (i.e., 1972-2003), the CPI and the PPI did not significantly affect the DJIA and S&P 500 index. The DJIA and the S&P 500 index did not affect the PPI or the CPI.

Serfling and Miljkovic (2011) researched the relationships among macroeconomic variables and the S&P 500 index. The relationship between the S&P 500 index and the CPI was influenced when one of the variables changed (Serfling & Miljkovic, 2011). The authors concluded that historical changes in the money supply, S&P 500 index, industrial production index, and the CPI could predict changes in the S&P 500 index. In addition, historical changes in interest rates, the S&P 500 index, dividend yield, CPI, and the money supply can be used in predicting changes in the CPI (Serfling & Milkovic, 2011).

2.3.1.3 The Industrial Production Index

The Industrial Production Index (IPI) is an indicator in the U.S. measuring the actual output from manufacturing, gas and electric utilities, and mining (Federal Reserve,

n.d.). It is published monthly by the Board of Governors of the Federal Reserve System. The index reports changes in production, and an increase in the index, in turn, shows growth in the manufacturing industries.

The IPI is extensively studied in relation to general economic development and the stock market. Sirucek (2012) observed a statistically significant relationship between the DJIA and the IPI. Indication on how industrial production affects stock market development was presented in the study conducted by Humpe and Macmillan (2007). In their study, they researched how macroeconomic variables affect stock market development in the U.S. and Japan. Their results indicated that the U.S. and Japanese stock markets were positively affected by industrial production. Further, interest rates and inflation negatively influenced the U.S. stock market, and the money supply negatively influenced the Japanese stock market.

Industrial production has also been studied in relation to developing countries. Rahman et al. (2009) studied how selected macroeconomic variables affect the stock market prices in the Malaysian stock exchange. The results from the study indicated that of the selected variables, industrial production strongly affected the development of stock market prices.

The IPI, together with other macroeconomic variables, and their historical values, can be used in predicting the stock market. Historical values of the IPI, interest rates, the money supply, CPI, and the S&P 500 index can be used in predicting current changes of the S&P 500 index (Serfling & Miljkovic, 2011). Even historical values of the S&P 500 index, interest rates, and the IPI can be used in predicting changes in the IPI.

2.3.2 Business Cycle Indicators

Business cycle indicators attempt to anticipate the economy's fluctuations. These indicators are often constructed by different variables attempting to forecast economic activity. Additionally, they can be used to forecast the peaks and troughs of the business cycle. The business cycle indicator included in this study is the OECD CLI.

2.3.2.1 The Composite Leading Indicator

The CLI is made by the OECD for most of the OECD countries. The CLI is used to predict turning points in the business cycle (OECD, 2021). The CLI's components are short-term economic indicators in the form of time series. The components of the CLI are leading indicators of the GDP (OECD, 2021). The composition of variables in the CLI depends on the country that its business cycles it measures. The choosing of the variables depends on certain criteria (Fichtner et al., 2009). The component must have an economic reason for the leading relationship with GDP. The component may cause business cycle fluctuations or measure economic activity at certain stages of the business cycle (for instance, early housing starts) (Fichtner et al., 2009). The component must lead the GDP, and the data must be timely. The number of components (5 to 11) in the CLI are country-specific (Fichtner et al., 2009). Additionally, the components of the CLI are weighted and make the CLI a diffusion index (OECD, 2021). The components of the U.S. CLI are the following: Weekly hours worked: manufacturing, Manufacturing-Industrial confidence indicators, Spread of interest rates, Consumer confidence indicator, Work started for dwellings, Net new orders-durable goods, and the share prices of the NYSE Composite (OECD CLI Turning Points of Reference Series and Component Series, 2021).

The CLI has been studied in relation to the stock market during different business cycle phases (Dzikevičius & Vetrov, 2011). The composition of different asset portfolios' risk and return are affected by how the assets are weighted in the portfolio and how they account for the fluctuations of the business cycle. If the business cycle fluctuations are considered while choosing the assets into the portfolio, it is possible to maintain the risk and return at levels chosen by the market participant (Dzikevičius & Vetrov, 2011). Additionally, the stage of the business cycle affects the stock market. In the recovery and expansion stage, the stocks are rising in value and they are affected favorably, while the stocks are affected negatively by the shrinking of the business cycle (Dzikevičius & Vetrov, 2011). Furthermore, reallocation of stocks in portfolios during recessions can help in keeping the risk at a manageable level (Dzikevičius & Vetrov, 2011).

Celebi & Hönig (2019) studied how different variables affect the German stock index DAX30 index. The OECD CLI for the German economy was one of the

variables the authors included in the study. Celebi and Hönig (2019) concluded that by conducting an OLS regression with a maximum of four lags, the variables influenced the DAX30 index returns. Further, the German OECD CLI was measured to have a positive relationship with the development of the DAX 30 index. The relationship was observed to be the strongest when the OECD CLI was numbered with three lags in the OLS regression.

2.3.3 Survey-based Indicators

The survey-based indicators use 'soft' data in gauging the opinions of their respondents. The indicators are constructed by surveys directed to participants in the manufacturing and service sectors (i.e., the PMIs) and to consumers (i.e., the Consumer Sentiment Index). The surveys ask how the economy is currently and how the respondents think that it will be in the future.

2.3.3.1 The Purchasing Managers' Index

The PMIs are survey-based indicators that measure trends in manufacturing and service sectors, and they are sent to the companies' executives that operate in the sectors (ISM n.d.a; IHS Markit, 2017). The surveys ask the executives if they think that the economic activity in the sectors is shrinking, continue to stay the same, or is expanding (ISM, n.d.a). The PMIs deliver information about the current economic situation and the future expectations that the executives have related to the industry in which the companies they work in operate. The first PMIs were surveys presented to companies operating in the manufacturing sector, and later PMIs have been developed for companies operating in the services sector as well. The most notable PMIs are developed by Markit Economics and by the Institute for Supply Management (ISM).

The PMIs values range from 0 to 100. The values between 0 and 49 state that the economic activity in the sector is shrinking. The value 50 means that economic

activity in the sector remains the same, and a value above 50 means that the economic activity is expanding in the sector (ISM, n.d.).

The PMIs are diffusion indices, with questions that are equally weighted in the index (ISM, n.d.a; IHS Markit, 2017). The areas that the questions cover depends on if the survey is directed to the manufacturing or service sector. The questions in the manufacturing PMIs are intended to specifically cover manufacturing-related areas, such as questions regarding employment, inventories, backorders, and supplier new deliveries (ISM n.d.a; IHS Markit, 2017). The questions in the service PMIs are related to the business activity, new orders, supplier deliveries, and employment (ISM, n.d.b).

The formula for the PMIs follows a general diffusion index:

$$PMI = (P1 * 1) + (P2 * 0.5) + (P3 * 0)$$

P1 in the formula represents the percentage of executives that report expansion, P2 represents the percentage of executives that have reported that the economic activity remains the same, and P3 represents the percentage of executives that have reported that the economic activity is shrinking. The number 1, 0.5, and 0 respectively stands for expansion, the economic activity remaining the same, and for the shrinking of the economic activity.

Previous studies examining the relationship between the stock market and PMIs have shown varying results. Dovolil (2016) studied the relationship and the predictive power of different economic indicators, including the PMI, in relation to the S&P 500 stock index. Dovolil (2016) observed that the PMI was lagging the S&P 500 index by one month. Johnson and Watson (2011) observed a statistically significant relationship between the manufacturing PMI published by the ISM and certain stock market returns. The PMIs forecasting ability has been demonstrated in relation to economic indices and the U.S. industrial economy (Jeon & Ji-Hong, 2017). Jeon and Ji-Hong (2017) demonstrated that the PMI has a positive relationship with the PPI and IPI in the U.S., that is, a change in the PMI often precedes a change in the PPI and IPI.

Hu et al. (2017) analyzed how variables affect the S&P 500 index futures. They asked 13 experts which variables market participants follow to determine when they

invest. One of the variables that the experts suggested that the market participants follow was the ISM manufacturing PMI. Hu et al. (2017) further analyzed how the variables affect the S&P 500 index futures and other futures. They concluded that market participants observe the ISM manufacturing PMI when investing in the S&P 500 index futures. The ISM manufacturing PMI has also affected the fluctuation of S&P 500 index futures and DJIA index futures, but other variables (e.g., US dollar index, interest rates) in the study had stronger explanatory power in the prediction of the rate of return of S&P 500 index futures (Hu et al. 2017).

In the current study, the ISM Manufacturing and Non-Manufacturing PMIs, IHS Markit Manufacturing PMI, and the Chicago PMI are included. The PMIs are included in the present study to answer the aim; to observe how similar indicators have performed before and during the pandemic. The PMIs will give regional (Chicago PMI) and national (all the other PMIs) perspectives to the current study.

2.3.3.2 The Consumer Sentiment Index

The Consumer Sentiment Index (CSI) measures consumer-related activities through a survey, and it describes consumer behavior and their expectations of the economy (Curtin, 2002). The index is survey-based, and it is published monthly. The idea behind studying the CSI in relation to the stock market development derives from that the consumers, with their spending and confidence, affect the economy and stock evaluation.

Otoo (1999) examined the relationship between the fluctuations of stock prices and the Consumer Confidence Index. Otoo observed that when companies increase in equity values, then consumer confidence increase. In addition, Otoo (1999) noted that consumers use the fluctuations of the stock market as an indicator of future economic development.

The relationship between the stock market and consumer sentiment can be divided into a long and short relationship depending on the timeframe. The long relationship between the stock market and consumer sentiment has been observed to be almost non-existent (Christ & Bremmer, 2003). However, there is a short relationship in

which the stock market affects consumer confidence. Christ and Bremmer (2003) propose in turn that expected changes in consumer sentiment are reflected in the stock market prices.

Charoenrook (2006) observed how consumer sentiment affects stock returns over the periods 1979-2000 and 1955-2000. The research observed that the consumer sentiment index could be used in the prediction of stock returns. Charoenrook (2006) concludes that the changes in consumer sentiment work best as a predictor for excess stock market returns at a timeframe of one month and at a timeframe of one year.

Table 2 Indicators and their sources

Category	*View*	*Indicator*	*Publisher and Source*
Survey-based indicators	Manufacturing (Business Cycle)	ISM Manufacturing PMI	Institute for Supply Managers / tradingeconomics.com
	Service (Business cycle)	ISM Non-Manufacturing PMI	Institute for Supply Managers / tradingeconomics.com
	Manufacturing and Service (Business Cycle)	Chicago PMI	Institute for Supply Managers - Chicago
	Manufacturing (Business Cycle)	IHS Markit PMI	IHS Markit / tradingeconomics.com
	Sentiment (Consumption)	The University of Michigan's Consumer Sentiment Index	The University of Michigan
Macroeconomic	Inflation (Consumption)	Consumer Price Index	Bureau of Labor Statistics
	Inflation (Production)	Producer Price Index	Bureau of Labor Statistics
	Production	Industrial Production Index	Board of Governors of the Federal Reserve System
Business cycle	Business Cycle	Composite Leading Indicator	OECD

3 Methodology

This section begins with the presentation of the research method and design of the present study. Further, the information about the data, variables and, how the data is transformed before analyzed in the study are presented. The section follows with the presentation of the different analytical methods in the study. It concludes by presenting the validity of the research method and threats to validity.

3.1 Research Method and Design

There are three general research methods identified by Creswell and Creswell (2018, pp. 41): quantitative, qualitative, and mixed research methods. According to Creswell and Creswell (2018), quantitative research tests measurable variables by examining their relationships. In addition, quantitative methods include statistical analyses and interpretations. Quantitative research methods usually examine relationships between different variables and attempt to understand the associations or the causality between them (Creswell & Creswell, 2018 pp. 206). Furthermore, in quantitative methods, the independent and dependent variables must be identified to describe the relationship between the variables (Creswell & Creswell, 2018 pp.206).

Creswell and Creswell (2018 pp. 49) identify that research methods include different research designs that provide an outline, which states the procedures of the different research methods. The different research methods can use many specific research designs. Three standard research designs are descriptive, exploratory, and casual designs (Cooper & Schindler, 2011). Exploratory design can be used when the problem does not have a clear definition, and there are no clearly defined hypotheses (Cooper & Schindler, 2011 pp.129). One of the main objectives of the descriptive research design is to discover associations among variables (Cooper & Schindler, 2011 pp. 134-135). The research methodology in the present study follows a quantitative research method with a part descriptive and part exploratory design.

3.2 Data, Time period, and Data sources

The including of the indicators for the present study are based on few criteria. The indicators must be researched in relation to stock market development. The indicators' data must be publicly available, either from the original sources or from third-party sources. Additionally, reputable institutions and organizations must publish the indicators. Furthermore, the indicators must measure some economic aspect of the U.S. economy.

The two stock market indices are the study's dependent variables, while the indicators are the independent variables. The time period of the data is from January 2019 to January 2021. The time period is chosen to notice if Covid-19 has caused observable short-term changes in the indicators' performance before and after the stock market crash in March 2020.

The indicator and stock market data are gathered from publicly available sources. The CPI and PPI data are gathered from the Bureau of Labor Statistics (BLS, n.d.b; BLS, n.d.d). The IPI data is gathered from Board of Governors of the Federal Reserve System (Board of Governors of the Federal Reserve System, n.d.). The Chicago PMI data is gathered from the Institute for Supply Managers - Chicago chapter (Institute for Supply Managers- Chicago n.d.). The OECD CLI data is gathered from the OECD (OECD, 2021). The ISM Manufacturing PMI and the ISM Non-Manufacturing PMI data are collected from the Institute of Supply Chain Management (ISM, n.d.a; ISM, n.d.b) and from the indicator website tradingeconomics.com (United States ISM Purchasing Managers' Index, n.d.; United States ISM Non-Manufacturing PMI, n.d.). The IHS Markit PMI data is gathered from the IHS Markit website and from the indicator website tradingeconomics.com (IHS Markit US Manufacturing Purchasing Managers' Index, n.d.). The University of Michigan's CSI data is gathered from the University of Michigan (University of Michigan, n.d.). Both stock indices are gathered from finance.yahoo.com (Dow Jones Industrial Average (2 February 2021); S&P 500 index (2 February 2021).

3.3 Variables

3.3.1 Independent Variables

3.3.1.1 Survey-based Indicators

The ISM Manufacturing PMI is an indicator that is published monthly by the Institute for Supply Chain Managers. It is an indicator based on a survey directed to purchasing managers in manufacturing companies. The survey is a composite indicator divided into five sections. The sections are the following: employment, production, inventories, new orders, and supplier deliveries (ISM, n.d.a).

The ISM Non-Manufacturing PMI is an indicator published monthly based on a survey directed to the purchasing managers in non-manufacturing companies (service sector). The ISM Non-Manufacturing PMI is a composite index with four sections: business activity, new orders, supplier deliveries, and employment (ISM, n.d.b).

The IHS Markit Manufacturing PMI is an indicator based on a survey directed to purchasing managers in manufacturing firms. The survey is divided into five differently weighted sections: output, employment, delivery times, new orders, and stocks of purchases. New orders and the questioned companies differ from the ISM manufacturing PMI (IHS Markit, 2017).

The Chicago PMI measures the economic activity of manufacturing and service industries around Chicago. It is an indicator based on a survey sent to purchasing managers in manufacturing and service companies in the Chicago area. It is a composite index with equally weighted parts. The survey is divided into new orders, production, order backlogs, supplier delivery, and employment (Institute for Supply Managers- Chicago, n.d.).

The CSI is published monthly by The University of Michigan, and it is a survey-based indicator. The survey consists of five questions asked to consumers regarding how they perceive their financial situation, how it is expected to change during the next year, how business conditions are expected to change during the next year and the next five years. Furthermore, when is it a preferable time to spend much money (University of Michigan, Surveys of Consumers n.d.).

3.3.1.2 Macroeconomic Indicators

The CPI measures the price difference of consumer products and services over time. The CPI used in the study is the consumer price index for all urban consumers with all items in American cities on average (BLS, n.d.a).

The PPI measures the changes in product prices of U.S. domestic production over time. The PPI included in the current study is the producer price index of final demand on all industries (BLS, n.d.c).

The IPI is a monthly published indicator in the U.S. It measures the output from manufacturing, gas and electric utilities, and mining. The index reports changes in the production and growth in the index show growth in manufacturing industries (Federal Reserve, n.d.).

3.3.1.3 Business Cycle Indicator

The OECD (CLI) is used to predict turning points in the business cycle). It is constructed by more minor economic and financial components, which can function as leading variables for the GDP. The OECD publishes composite leading indicators for almost all OECD member countries (OECD, 2021).

3.3.2 Dependent Variables

The stock market is represented by the price-weighted Dow Jones Industrial Average (DJIA) stock index and the value-weighted Standard & Poors' 500 stock index (S&P500 index). The S&P 500 index includes 500 companies covering almost all market capitalization in the U.S. (Standard & Poors' 500 index factsheet, n.d.). The DJIA, in turn, covers 30 multinational companies that act in all industries except transportation and utilities (The Dow Jones Industrial Average factsheet, n.d.).

3.4 Data pre-processing

Before the analyses can be conducted in the present study, the indicators' data and the stock indices' data must be transformed. The indicators are transformed based on their index type (See Table 3). Depending on the indicator, different transformations are conducted. Additionally, indicators that are volume indices have different base periods. Therefore, the base periods must be transformed so that they show accurate measurements for the time period of the present study. Further, these indicators' base periods are calculated to the base periods of January 2019. The new base period for the volume indices will be calculated by the following formula:

$$\textit{New Index Value} = (\textit{Old Index Value} / \textit{New Base Value of Index}) \times 100 \qquad (3.1)$$

Furthermore, the stock indices' data must be transformed. The data is composed of the stock indices' daily closing prices. Further, the stock indices' closing prices are published daily, while all the indicators included in the current study are published monthly. The stock indices' data is transformed instead of the indicators' data, due to that daily data is easier to transform to monthly data. Therefore, the stock indices' daily closing prices are transformed by calculating the arithmetic mean of the daily closing prices for each month of the time period of the current study. This makes the indicators and the stock indices comparable in analyses.

Depending on the index type, further data transformation is done. The natural logarithm is used to stabilize the variance (Shumway & Stoffer, 2011 pp.63).

$$\ln x \qquad (3.2)$$

Logarithmic transformation is conducted to both stock indices and the following indicators: PPI, CPI, IPI, and the CSI. The PMIs and the OECD CLI are diffusion indices, where the change between two index values is already measured. Further, another technique that is used to transform the data to exhibit stationarity is first differencing.

$$Y(i) = X(i) - X(i-1) \qquad (3.3)$$

First differencing is performed to all the indicators and to the two stock market indices. Differencing is usually used to exclude the non-stationary behavior time series exhibit (Shumway & Stoffer, 2011 pp.62). Log transformation (for chosen variables) and differencing (for all variables) help in making the indicators and stock market indices stationary and prepared for further analysis.

Table 3 Indicators, stock indices and the data pre-processing operations

Category	*Stock index & Indicator*	*Index type*	*Operation*
Stock market index	S&P 500 index	Volume Index	Natural logarithm First difference
	DJIA	Volume index	Natural logarithm First difference
Survey-based indicators	ISM Manufacturing PMI	Diffusion index	First difference
	ISM non-manufacturing PMI	Diffusion index	First difference
	Chicago PMI	Diffusion index	First difference
	IHS Markit PMI	Diffusion index	
	The University of Michigan's consumer sentiment index	Volume index	Natural logarithm First difference
Macroeconomic	Consumer Price Index	Volume index	Natural logarithm First difference
	Producer Price Index	Volume index	Natural logarithm First difference
	Industrial Production Index	Volume index	Natural logarithm First difference
Business cycle	OECD CLI	Diffusion index	First difference

3.5 Correlation

Correlations are conducted to measure how the stock indices move in relation to the indicators. Correlation presents the strength of the association between two variables, but it does not show the strength of causation nor if the variables are affected by some other factors. In this study, the Pearson correlation method is used. The Pearson correlation method measures the correlation between the values of -1 and 1 (Nettleton, 2014). The value of 0 informs of no correlation. The value of -1 informs a perfect negative correlation in which the two variables move in opposite directions. The value of 1 informs a perfect positive correlation in which two variables move in the same direction. Correlation informs of the linear relationship between the variables (Nettleton, 2014). The relationship between the stock indices and the indicators shall be observed first by using correlation and then cross-correlation

Correlation and the correlation significance will also be tested between the independent variables of the study. The independent variables that have the lowest correlation and correlation significance among themselves will be used later in multiple linear regression analysis. High correlation values between independent variables indicate that a change in one of the independent variables may cause a change in another independent variable. This will cause the regression model to contain flaws which will reduce the precision of the model.

3.6 Cross-correlation

Cross-correlation measures similarities in two time series, and it is used to map lag- and lead relationships between the time series (Shumway & Stoffer, 2011 pp.26). The leading X_{t-1} and lagging X_{t+1} relationship are expressed in correlations between the two time series with values between -1 and 1. Cross-correlation is used in gaining information at which time the two time series correlate the most. The relationship between the indicators and the stock indices will be further analyzed by cross-correlation. This will show how and in what way the indicators can be used in the prediction of the stock market indices. The strongest correlation and at what time this

occurs will be measured, and the indicators' ability to serve as leading, coincident, or lagging indicators will be further observed.

3.7 Regression Models

Four different regression models will be conducted in the analysis. Firstly, a simple linear regression model to observe the level of significance a single independent variable has on the dependent variables. Secondly, a simple linear regression model that uses lagged values. The lagged values will be obtained from the cross-correlation analysis. The lagged variables that have the highest correlation values will be used in the lagged simple linear regression model. The indicators that will be chosen for the multiple linear regression will be chosen by the results from the correlation and correlation significance test between the independent variables. The indicators that correlate the least and have the smallest correlation significance levels with each other will be chosen for the multiple linear regression model.

The simple linear regression shows the relationship between the dependent variable and a single independent variable. The Y_i is the predicted dependent variable value, X_i is the independent variable, β_1 is the slope of the line, β_0 is the intercept, and the ϵ is the error estimate (Shumway & Stoffer, 2011 pp.48).

$$Y_i=\beta_0+\beta_1 X_i+\epsilon \qquad (3.4)$$

Multiple linear regressions will be conducted with the coincident correlation values of the indicators and with lagged values. The lagged values will be taken from the cross-correlation analysis. The Y_i is the dependent variable, X_i are the independent variables, β_0 is the intercept, each dependent variables slope coefficient βp, and ϵ is the error term (Shumway & Stoffer, 2011 pp.48).

$$Y_i=\beta_0+\beta_1 X_{i1}+\beta_2 X_{i2}+\ldots+\beta_p X_{ip}+\epsilon \qquad (3.5)$$

The simple linear regression models measure how single variables affect the variation in the stock indices, while the multiple regression models measure how many independent variables can measure the variation of the stock indices' values.

3.9 R and R Packages

The analysis of the data was performed using the software R (R Core Team, 2020). A combination of the R software's base operations and operations from other packages was performed throughout the analysis of the data. Operations from the package *dplyr* were performed to the collected data, so that the indicators and stock market indices were comparable (Wickham et al., 2020) (see section *Data pre-processing*). For the visualizations of the indicators and stock market indices' data the package *ggplot2* was used (Wickham, 2016). For the correlations and regression models, the analyses were performed mainly by operation from the base package of R. However, operations from the package *dynlm* were also performed for the regressions (Zeiles, 2019).

3.10 Validity and Threats

Validity in research determines how accurately the researched concept or construct is measured (Heale & Twycross, 2015). The aspects regarding the validity of research depend on what type of research is performed (Roe & Just, 2009). For instance, the validity is affected if the research is performed as quantitative or qualitative research and if the research is conducted as experiments or surveys. That is, the research approach and structure affect the validity.

Validity can be categorized in many ways. For the present study and for quantitative and qualitative studies in general, external and internal validity are aspects of validity that influence the research method. According to Roe and Just (2009), internal validity concerns that the correlations in a study are of causal nature. This implies that the independent variables can be proven to influence the dependent variables. External validity, in turn, concerns that the results from the study can be generalized outside the study to other studies, people, and concepts. Furthermore, validity can be divided into subtypes, such as criterion validity, construct validity, content validity, and face validity (Taherdoost, 2016). Criterion validity can further be divided into predictive validity, concurrent validity, and postdictive validity. Similarly, construct

validity can be further divided into discriminant validity and convergent validity (Taherdoost, 2016).

Heale and Twycross (2015) argue that content validity, construct validity, criterion validity, and their subtypes affect quantitative research. Content validity can be described as the extent to which an instrument in a study accurately measures all the content in relation to a variable. Construct validity can be described as the extent to which an instrument measures the variable. Criterion validity refers to how the instrument correlates with other instruments that measure the same variable, that is, how related they are (Heale & Twycross, 2015).

Internal- and external validity is affected by threats (Jenkins-Smith et al., 2017). For instance, the variables included in a study may or may not affect and explain the phenomena that are researched. Correlation may be discovered with variables in a study, but not causation. There can be other factors that affect the researched phenomena that are not included in the study, and these factors could be determined afterward to be of major importance. All this can be described to be threats that affect the external- and internal validity of the study. Jenkins-Smith et al. (2017) present regular threats to the external- and internal validity. Threats for internal validity can be categorized into these different categories: History; unexpected events that occur during the experiment can affect the researched subject or dependent variable. Maturation: Changes that can affect the dependent variable or participants in a study, such as aging. Selection bias: to reduce selection bias in a study, randomization of the participants can be performed. Experimental mortality: Participants can cancel their participation in a study. Statistical regression: extreme scores in regression models can move towards the mean. Instrumentation: The measurement process is changed, or it is unreliable. Testing: pre-test results can influence the results in a test (Jenkins-Smith et al., 2017).

Threats for external validity are described as following by Jenkins-Smith et al. (2017): Testing; Pre-testing or other tests and measurement can affect similar tests and measurements. Experimental setting: The participants may be affected by the setting and not act normally because of it, making the results untransferable from the experiment. Sample representation: The sample may reflect the population poorly, undermining the possibility to generalize the results. Interaction of selection bias and

experimental treatment: selection bias in the choice of participants in a study can lead them to be sensitive to the experiment, altering the results of a study. Interaction with testing: The participants can be influenced by a test in a study affecting the results of another test, which, in turn, can influence the generalization of the test (Jenkins-Smith et al., 2017).

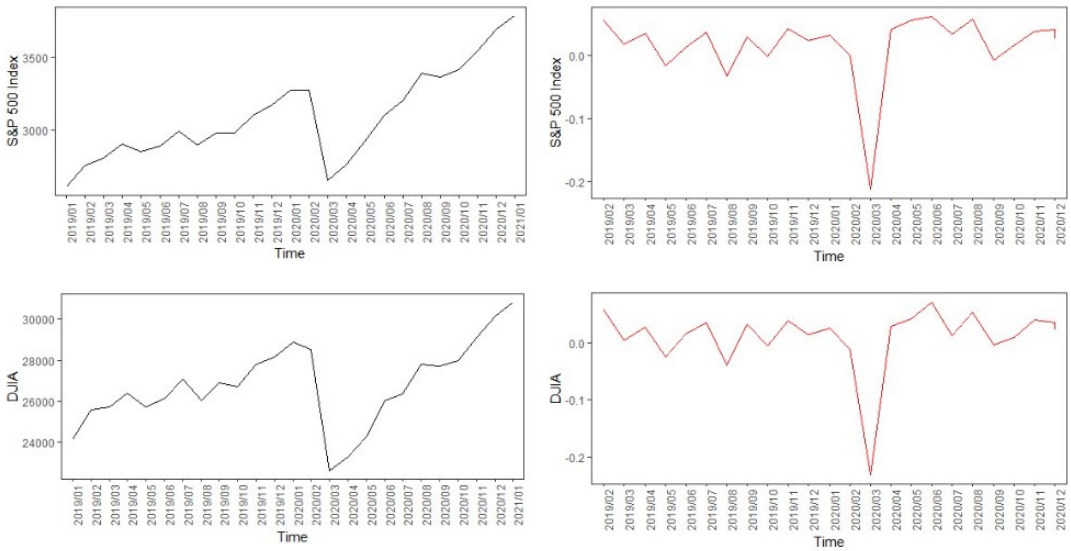

Chart 1 The stock indices before and after data pre-processing.

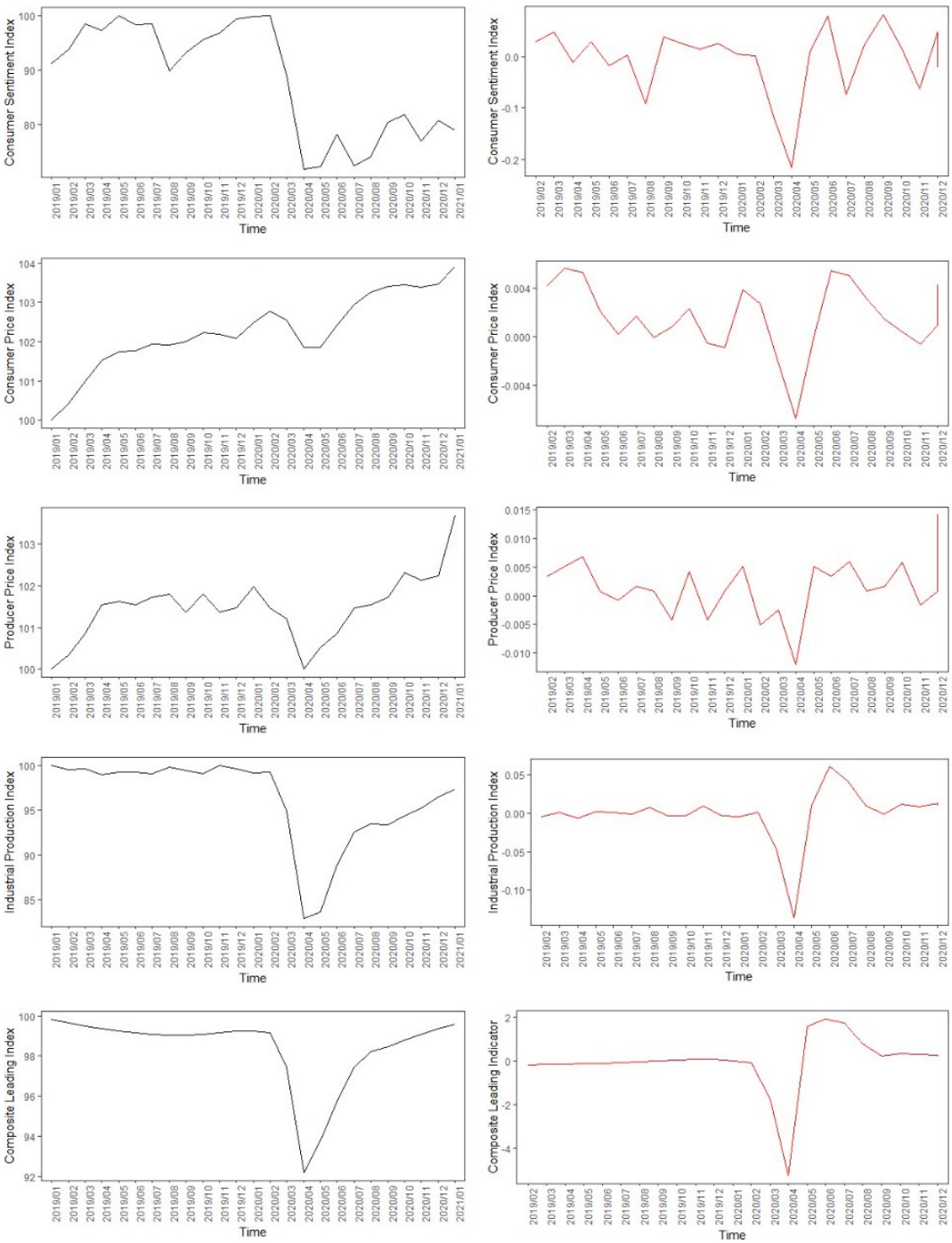

Chart 2 The macroeconomic indicators, the CSI, and the CLI before and after data pre-processing.

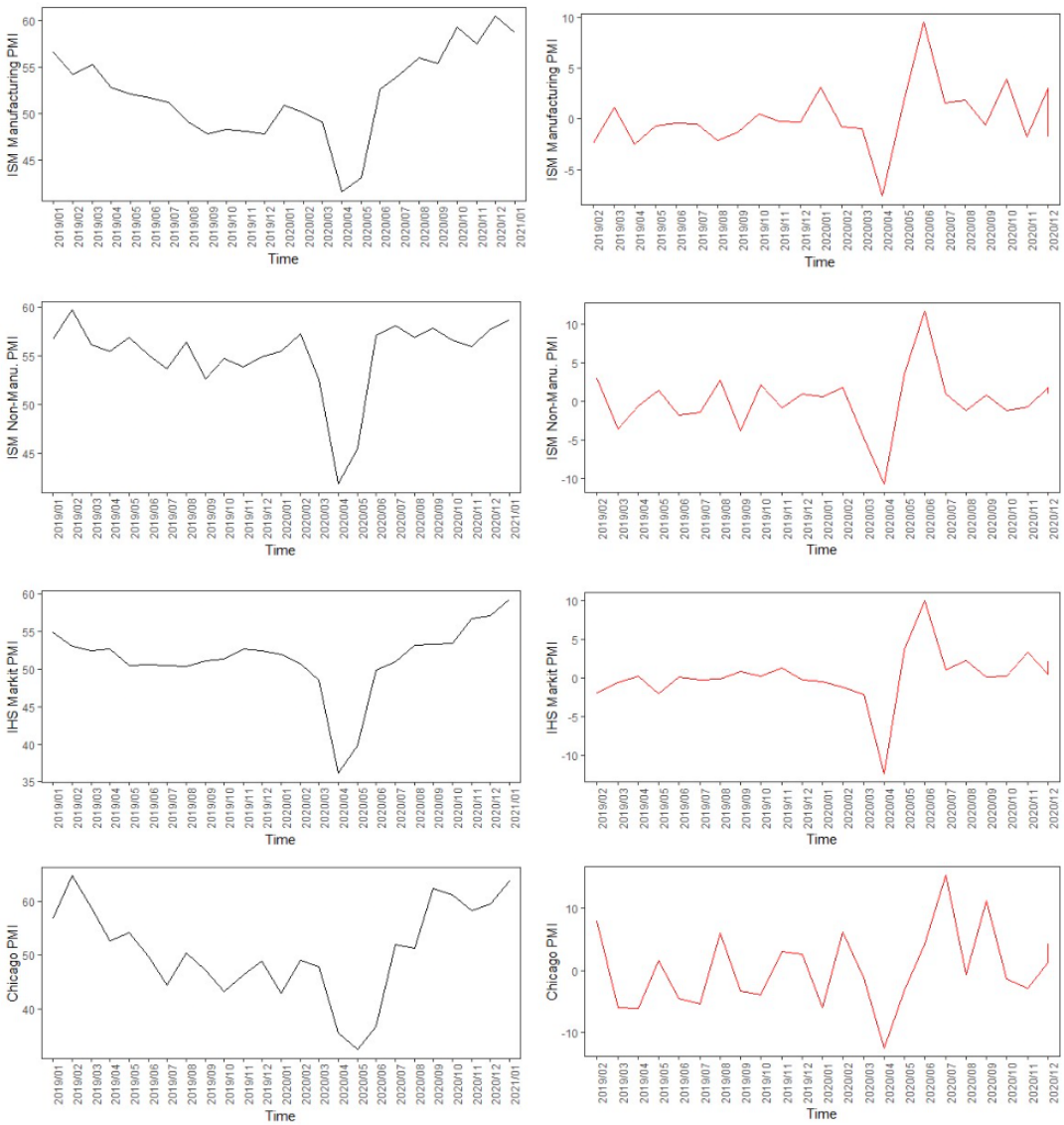

Chart 3 The PMIs before and after data pre-processing.

4 Empirical findings

The empirical findings of the study are presented according to the performed analytical method. The findings are briefly discussed and compared in this section. A deeper analysis and discussion of the results are performed in the fifth section of the present study. This section begins with presenting the results from the correlation of the indicators with the stock indices. It continues by presenting the results from the indicators' correlation and correlation significance test and by the cross-correlations. The results from the regression models are presented last.

4.1 Indicators' Correlations with the Stock Indices

Table 4 presents the nine indicators' correlations with the two stock market indices. Each indicator is correlated individually with the two stock market indices.

Table 4 Indicators' correlations with the stock indices

	S&P 500 Index	*DJIA*
ISM Manufacturing PMI	.175	.194
ISM Non-Manufacturing PMI	.259	.292
IHS Markit PMI	.233	273
Chicago PMI	-.039	-.029
PPI	.164	.154
CPI	.289	.291
IPI	.260	.284

CSI	.333	.376
CLI	.292	

The indicators with the highest correlation with the S&P 500 index are the CSI, the CLI, and the CPI. Interestingly, the highest positive correlations are with indicators belonging to different categories. Furthermore, all the macroeconomic indicators show positive correlations with the S&P 500 index, while the survey-based indicators show more variation in their correlation values. The CSI has the highest positive correlation, followed by the ISM Non-Manufacturing PMI, the IHS Markit PMI, and the ISM Manufacturing PMI. The Chicago PMI shows a low negative correlation with the S&P 500 index.

The CSI has the highest positive correlation with the DJIA, followed by the CLI and the ISM Non-Manufacturing PMI. Furthermore, all the macroeconomic indicators show a positive correlation with the DJIA, whereas the PPI has the lowest correlation. There is more variation in the correlation values of the survey-based indicators and the DJIA. The CSI has the highest positive correlation, followed by the ISM Non-Manufacturing PMI, the IHS Markit PMI, ISM Manufacturing PMI, and the Chicago PMI.

The indicators' correlations with the DJIA present similar results as the indicators' correlations with the S&P 500 index. The similar results can be explained by the almost identical development of the stock market indices during the timeframe of 2019 to 2021.

The indicator that displays the lowest correlation values with the stock market indices is the Chicago PMI. Further, the Chicago PMI displays slightly negative correlation values with the stock market indices. It can be explained by that the Chicago PMI measures regional companies' economic activities, which do not reflect the national companies' economic activities listed on the DJIA and S&P 500 index.

Interestingly, the indicator that has the highest positive correlation with both stock market indices is the CSI. The CSI describes consumer behavior and their expectations of the economy (Curtin, 2002), and the consumers' expectations have

been negatively affected by Covid-19. Furthermore, this could explain the high positive correlation the CSI has with the stock indices, especially by connecting the stock market crash and fallen consumer sentiment.

4.2 The Indicators' Correlation and Correlation Significance

Table 5 displays the indicators' correlations and correlation significances. The correlation and correlation significance analysis of the indicators will decide which indicators will be included as the independent variables in the multiple linear regression models. Furthermore, the exclusion of indicators that display too high correlation and correlation significance from the multiple linear regression models will make the models more precise.

The indicators that display the highest correlation with other indicators are the CLI, the IPI, and the IHS Markit PMI. These three indicators will be excluded from the multiple linear regression models. Additionally, many other indicators display high correlation significances, which would affect the precision of the multiple linear regression models. Therefore, other indicators that will be excluded from the multiple linear regression models are the ISM Manufacturing PMI, ISM Non-Manufacturing PMI, and the CPI. The exclusion of these indicators will minimize the multicollinearity in the multiple linear regression models. The indicators that are excluded from the multiple regression models belong to the different indicator categories.

Table 5 Indicators' correlation and correlation significance

Independent variables	*Chicago PMI*	*CLI*	*IHS Markit PMI*	*CPI*	*ISM Non-Manu. PMI*	*IPI*	*PPI*	*CSI*	*ISM Manu. PMI*
Chicago PMI	1	.51*	.35	.36	.54**	.55**	.26	.26	.23
CLI	.51*	1	.90****	.68***	.78****	.97*****	.61**	.69***	.73****
IHS Markit PMI	.35	.90*****	1	.57**	.78****	.89*****	.51*	.62**	.77****

CPI	.36	.68***	.57**	1	.57**	.71****	.72***	.60**	.51*
ISM Non-Manu. PMI	.54**	.78****	.78****	.57**	1	.79****	.48*	.59**	.69***
IPI	.55**	.97****	.90****	.71***	.79****	1	.59**	.68***	.77***
PPI	.26	.61**	.51*	.72***	.48*	.59**	1	.41*	.41*
CSI	.26	.69***	.62**	.60**	.59**	.68****	.41*	1	.62**
ISM Manu. PMI	.23	.73****	.77****	.51*	.69***	.75****	.41*	.62**	1

Signif. codes:

p ≤ .0001 '****' p ≤.001 '***' p≤ .01 '**' p ≤ .05 '*'

The indicators that will be included in the multiple linear regression models are the CSI, the PPI, and the Chicago PMI. Furthermore, these indicators will be assigned as the independent variables in the multiple linear regression models. Interestingly, two indicators belonging to the survey-based category and one to macroeconomic will be included in the multiple linear regression models. The indicators' correlation and correlation significance test display that the CSI, the PPI, and the Chicago PMI are not as likely to be affected by changes in other indicators as indicators with high correlation and correlation significance.

4.3 Cross-correlations

Table 6 presents the cross-correlations between the indicators and the DJIA. The lagging months are shown under positive lags, and the leading months are shown under the negative lags. The bolded values are the highest positive correlations.

Table 6 Cross-correlations with the indicators and the DJIA

	4	*3*	*2*	*1*	*0*	*-1*	*-2*	*-3*	*-4*
ISM M. PMI	-.033	-.619	.039	**.571**	.194	.063	-.222	.017	-.025
ISM Non-M. PMI	-.115	-.576	-.142	**.688**	.292	-.080	-.066	-.120	-.055
IHS Markit PMI	-.093	-.546	-.043	**.706**	.273	.047	-.056	.020	-.205
Chicago PMI	-.471	-.056	.179	**.588**	-.029	-.119	.149	-.134	-.028
PPI	-.146	-.110	.001	**.664**	.154	.206	-.295	.016	.042
CPI	-.305	-.230	.262	**.707**	.291	-.230	-.281	.083	.089
IPI	-.247	-.368	.087	**.862**	.284	-.040	-.143	-.055	-.148
CSI	.158	-.186	.011	**.656**	.376	- .159	-.106	-.195	-.118
CLI	-.262	-.292	-.081	**.858**	.305	.008	-.166	-.032	-.115

The indicators in Table 6 display the highest correlation values under +1 positive lag with the DJIA. In other words, the indicators are lagging the DJIA with one month. The indicators that have the highest positive correlation under the +1 lag are the IPI, the CLI, and the CPI. Additionally, due to that, the highest positive correlation values are under the +1 lag, the indicators display almost no leading abilities in relation to the DJIA. However, some minor positive correlation values between the DJIA and the indicators during leading months can be observed. Notably, the PPI with a positive correlation value of 20% under the leading lag of -1. However, the correlation values under the leading months are too minor to affect the development of the DJIA.

Table 7 Cross-correlation with the indicators and the S&P 500 index

	4	*3*	*2*	*1*	*0*	*-1*	*-2*	*-3*	*-4*
ISM M. PMI	-.048	-.605	.057	**.585**	.175	.067	-.193	-.037	-.017
ISM Non-M. PMI	-.114	-.593	-.130	**.716**	.260	-.082	-.033	-.155	-.080
IHS Markit PMI	-.082	-.542	-.062	**.737**	.233	.034	-.023	-.041	-.211
Chicago PMI	-.464	-.075	.219	**.574**	-.038	-.124	.153	-.142	-.056
PPI	-.192	-.089	-.010	**.660**	.164	.181	-.287	-.030	.035
CPI	-.323	-.228	.266	**.719**	.289	-.232	-.288	.041	.058
IPI	-.252	-.366	.082	**.862**	.260	-.069	-.124	-.107	-.171
CSI	.148	-.228	.021	**.665**	.333	-.178	-.077	-.228	-.141
CLI	-.264	-.286	-.087	**.866**	.292	-.033	-.137	-.080	-.142

From Table 7 can be observed that the indicators' highest positive correlations are under the +1 lagging month. Further, the indicators that have the highest positive correlations are the CLI, the IPI, and the IHS Markit PMI.

The cross-correlations between the indicators and the DJIA (see Table 6), and the cross-correlations between the indicators and the S&P 500 index (see Table 7) display similarities. In both analyses, the highest positive correlations are under the +1 lag. Furthermore, this implies that the indicators are lagging the stock market indices by one month. Additionally, almost no leading abilities can be observed for the indicators, and the correlations that can be observed under the leading lags are too minor to affect the development of the S&P 500 index and the DJIA.

4.4 Simple Linear Regression and Lagged Simple Linear Regression

The intention of the simple linear regression models is to determine how significant the effect the indicators have in relation to the S&P 500 index and the DJIA. Firstly, the results from simple linear regression models are presented. Secondly, the lags with the highest positive correlation values from the cross-correlations are included for the indicators in simple linear regression models with lagged variables. The purpose of performing simple linear regressions with lagged values is to observe if the lagged values generate a better fit for the model.

Table 8 displays the simple linear regressions between the nine indicators and the DJIA.

Table 8 Simple linear regressions with the indicators as independent variables and the DJIA as the dependent variable

Independent variable	*Intercept* p-value	*p-value*	*F-stat*	R^2	*Adjusted* R^2
ISM Manufacturing PMI	.412	.365	.857	.037	-.006
ISM Non-Manufacturing PMI	.403	.167	2.05	.085	.043
IHS Markit PMI	.426	.198	1.77	.074	.032
Chicago PMI	.403	.168	.019	.000	-.045
PPI	.549	.472	.536	.024	-.021
CPI	.952	.168	2.03	.085	.043
IPI	.363	.179	1.93	.080	.039
CSI	.289	.070.	3.62	.141	.102
CLI	.377	.147	2.255	.093	.052

Signif. codes:

p ≤.0001 '***' p ≤ .001 '**'p ≤ .01 '*'p ≤ .05 '.'

Performing the simple linear regression with coincident times for the independent and dependent variables displays mostly nonsignificant values with one exception. The exception being the CSI, with a p-value of $p < .05$. The CSI also has the highest explanatory power of 14% (10% adjusted multiple R^2). However, from the results can be observed that the indicators do not explain the variation of the DJIA when using coincident times for the indicators.

Table 9 Simple Linear regressions with the indicators as independent variables and the S&P 500 index as the dependent variable

Independent variable	*Intercept p-value*	*p-value*	*F-stat*	R^2	*Adjusted* R^2
ISM Manufacturing PMI	.181	.413	.697	.031	-.013
ISM Non-Manufacturing PMI	.173	.221	1.59	.067	.025
IHS Markit PMI	.185	.274	1.26	.054	.011
Chicago PMI	.177	.858	.033	.002	-.044
PPI	.275	.444	.609	.027	-.017
CPI	.585	.171	2.01	.084	.042
IPI	.154	.220	1.60	.068	.025
CSI	.120	.112	2.74	.111	.070
CLI	.158	.166	2.05	.085	.044

Signif. codes:

$p \leq .0001$ '***' $p \leq .001$ '**' $p \leq .01$ '*' $p \leq .05$ '.'

The results of the simple linear regression with the indicators and the S&P 500 index as the dependent variable are displayed in Table 9. The results are similar to the

simple linear regression with the DJIA as the dependent variable (see Table 8). All the indicators have a nonsignificant effect on the S&P 500 index.

Performing the simple linear regressions with coincident times for the independent variables shows nonsignificant effects on the development of the DJIA and the development of the S&P 500 index. In conclusion, using coincident times for the indicators is unreliable in explaining the development of the values of the S&P 500 index and the DJIA.

Table 10 Simple linear regression with lagged independent variables and the DJIA as the dependent variable

Independent variable	*Intercept p-value*	*p-value*	*F-stat*	R^2	*Adjusted* R^2
ISM Manufacturing PMI	.4720	.0036 **	10.67	.3370	.3054
ISM Non-Manufacturing PMI	.2745	.0002 ***	19.85	.4859	.4614
IHS Markit PMI	.4634	.0001 ***	21.66	.5077	.4842
Chicago PMI	.3324	.0020**	12.39	.3710	.3410
PPI	.9150	.0005***	16.78	.4442	.4177
CPI	.2236	.0001***	22.79	.5204	.4976
IPI	.0957	.0001***	61.6	.7458	.7337
CSI	.1550	.0005 ***	16.29	.4368	.4100
CLI	.1420	.0001***	59.31	.7385	.7261

Signif. codes:

p ≤. .0001 '***' p ≤ .001 '**' p ≤ .01 '*' p ≤ .05 '.'

Performing the simple linear regression with lagged independent variables (t+1) shows that all the indicators have a significant effect on the development of the DJIA. The CLI, the IPI, the CSI, the CPI, the PPI, the IHS Markit PMI, and ISM

Non-Manufacturing PMI show very strong significances (p ≤ .0001). The ISM Manufacturing PMI and the Chicago PMI show a strong significance (p ≤ .001). In conclusion, the indicators' explanatory power is stronger when lagged, than when using coincident times.

Table 11 Simple linear regression with lagged independent variables and the S&P 500 index as the dependent variable

Independent variable	*Intercept p-value*	*p-value*	*F-stat*	R^2	*Adjusted* R^2
ISM Manufacturing PMI	.1820	.0027 **	11.5	.3538	.323
ISM Non-Manufacturing PMI	.0680	.0001 ***	23.32	.5262	.5037
IHS Markit PMI	.1380	.0001 ***	25.92	.5524	.5311
Chicago PMI	.1197	.0028 **	11.46	.3530	.3222
PPI	.5776	.0005 ***	16.43	.4390	.4123
CPI	.5280	.0001 ***	24.44	.5379	.5159
IPI	.0114 *	.0001***	61.57	.7457	.7336
CSI	.0399 *	.0005 ***	17.08	.4485	.4222
CLI	.0165*	.0001 ***	63.4	.7512	.7393

Signif. codes:

p ≤ .0001 '***' p ≤ .001 '**' p ≤ 0.01 '*'p ≤ 0.05 '.'

The IPI, the CLI, the IHS Markit PMI, the CPI, the ISM Non-Manufacturing PMI, the CSI, and the PPI show very strong significance (p ≤ .0001). Further, the Chicago PMI and the ISM Manufacturing PMI show strong significances (p ≤ .001).

Interesting changes can be perceived when simple linear regressions are conducted with lagged independent variables. All the indicators generate a better fit, show strong significances, and present higher R^2. The cross-correlations (see Tables- 6 and

7) showed that the indicators lagged by (t+1), and the results from the simple linear regression models with lagged independent variables effectively strengthened the notion that the indicators do lag the stock indices during January 2019 to January 2020. In other words, the stock indices have fluctuated before the indicators, and the indicator values have moved afterward, showing that no leading abilities can be observed.

4.5 Multiple Linear Regression

Table 12 presents the multiple linear regression with the S&P 500 index as the dependent variable. The independent variables are chosen based on their correlation and correlation significance values (see Table 5).

Table 12 Multiple linear regression with the S&P 500 index as the dependent variable

Independent variables	*p-value*	*Estimate*	*Std.error*	*T value*
Intercept	.171	.0168	.0118	1.419
Chicago PMI	.517	-.0012	.0018	-.659
PPI	.803	.6198	2.447	.253
CSI	.152	.2836	.1902	1.491

Signif. codes:

p ≤ .0001 '***' p ≤ .001 '**'p ≤ .01 '*' p ≤ 0.05 '.'

Dependent variable: S&P500 index

p-value	*F stat*	*R^2*	*Adjusted R^2*
.4131	1	.1305	$5.509e^{-05}$

The multiple linear regression model with the S&P 500 index as the dependent variable show no significant results. Furthermore, the indicators in the model cannot explain the variation of the S&P 500 index.

Table 13 Multiple linear regression with the DJIA as the dependent variable

Independent variables	*p-value*	*Estimate*	*Std.error*	*T value*
Intercept	.3348	.0122	.0124	.988
Chicago PMI	.5189	-.0013	.0019	-.657
PPI	.9136	.2813	2.559	.110
CSI	.0932.	.3507	.1989	1.763

Signif. codes:

p ≤ .0001 '***' p ≤ .001 '**'p ≤ .01 '*' p ≤ 0.05 '.'

Dependent variable: DJIA

p-value	*F stat*	R^2	*Adjusted* R^2
.3134	1.264	.1594	.0334

The indicator that performs the best in the multiple linear regression model with the DJIA as the dependent variable is the CSI. The CSI displays a significant result, while the other indicators do not. This, however, do not explain the development of the DJIA.

The simple linear regression models (see Tables- 8 and 9) and the multiple regression models (Tables- 12 and 13) display, that using coincidental times for the independent variables make the models unsuitable in describing the development of the stock indices. Therefore, the two following multiple linear regression models use the lagged values from the cross-correlations.

Table 14 Multiple linear regression with lagged independent variables and the DJIA as the dependent variable

Independent variables	*p-value*	*Estimate*	*Std.error*	*T value*
Intercept	.3802	.0058	.0065	.898
Chicago PMI	.0015**	.0039	.0011	3.712
PPI	.0029**	4.558	1.331	3.424

CSI	.0034**	.3464	.1035	3.345

Signif. codes:

p ≤ .0001 '***' p ≤ .001 '**'p ≤ .01 '*' p ≤ 0.05 '.'

Dependent variable: DJIA

p-value	*F stat*	*R^2*	*Adjusted R^2*
*.0001****	22.95	.7837	.7495

Conducting the multiple linear regression with lagged independent variables shows that all the indicators in the model have a statistically significant effect. The explanatory power of the model is 78% (Adjusted R^2 is .75). The independent variable with the highest significance level is the Chicago PMI, followed by the PPI and the CSI. The model indicates that changes in the indicators correlate with changes in the DJIA.

Table 15 Multiple linear regression with lagged independent variables and the S&P 500 index as the dependent variable

Independent variables	*p-value*	*Estimate*	*Std.error*	*T value*
Intercept	.0748.	.0118	.0063	1.885
Chicago PMI	.0024**	.0035	.0010	3.492
PPI	.0037**	4.222	1.275	3.312
Consumer sentiment	.0029**	.3383	.0992	3.411

Signif. codes:

p ≤ .0001 '***' p ≤ .001 '**'p ≤ .01 '*' p ≤ 0.05 '.'

Dependent variable: S&P 500 index

p-value	*F stat*	*R^2*	*Adjusted R^2*
*.0001****	21.88	.7755	.7401

The multiple linear regression model with the S&P 500 index as the dependent variable and the indicators as lagged variables displays significant results. The

Chicago PMI has the highest significance level, followed by the CSI and the PPI. The explanatory power of the model is circa 77% (Adjusted R^2 is .74).

The results from the multiple linear regression models with lagged independent variables display similarities. The models show an adjusted R^2 nearing 75% (74% and 74.95%, respectively), and the indicators have similar p-values. The similarities can be mainly explained by the similar development of the stock indices during the time period of January 2019 to January 2021.

The findings from the cross-correlation analyses imply that the indicators could not be used in predicting the stock indices' values and that they have been lagging the stock indices. This notion has been enhanced by the results from the regression models and by the difference in the results when the regressions are performed with and without lagged variables. In conclusion, the analyses have shown that the indicators lag the stock market indices.

5 Discussion

The empirical findings are further analyzed and linked to the previously presented theories and studies in this section. The section starts by discussing factors associated with the stock market crash and factors that have affected the indicators. Further, the section continues in discussing the results of individual indicators according to which group they belong to.

The Covid-19 pandemic caused a shock that continues to affect companies' economic activities and countries' economies. The stock market was early to be affected, eventually leading to the stock market crash in March 2020. The reasons for the crash can be argued to be caused by many factors. The pandemic led to widespread uncertainty, and market participants started to expect the worst that could occur. Furthermore, the regulations and restrictions that governments implemented to combat the virus further increased the uncertainty. Additionally, the economic activities of companies were restricted, and the companies had to implement new policies to continue operating under new regulations. However, the regulations did not directly affect the stock market, but different economic factors associated with the indicators

The stock market could have been affected by a decline in liquidity and large amounts of debt. The federal reserve started to provide more liquidity to the market to encourage participation in the financial markets (Cox, 2020). Additionally, stock market liquidity has shown to decrease before the business cycle has started a turning point for recessions (Naes et al., 2010). One may also argue that the assets may have also been too overvalued and in need of a correction.

The S&P 500 index and DJIA return predictability and price volatility have been determined to be affected by a structural break during the onset of the pandemic (Hong et al., 2021). Hong et al. (2021) argued that the break occurred explicitly during the selling of stocks by members of the U.S. Senate before the stock market crash of March 2020. Additionally, after the break, the predictability of returns and price volatility increased. Hong et al. (2021) describe that the stock market crashed after the U.S. senate members sold their stocks, highlighting information asymmetry between market participants. The price volatility had a similar development as the

stock market returns predictability. Furthermore, Hong et al. (2021) conclude that the stock market was affected by market inefficiency. In other words, the stock market lacked efficiency in respect to the lack of information the market participants had. Additionally, it can be argued that the stock market prices did not accurately reflect their intrinsic value, affecting the risks and returns for market participants, leading to implications to the risks and returns associated with asset pricing models.

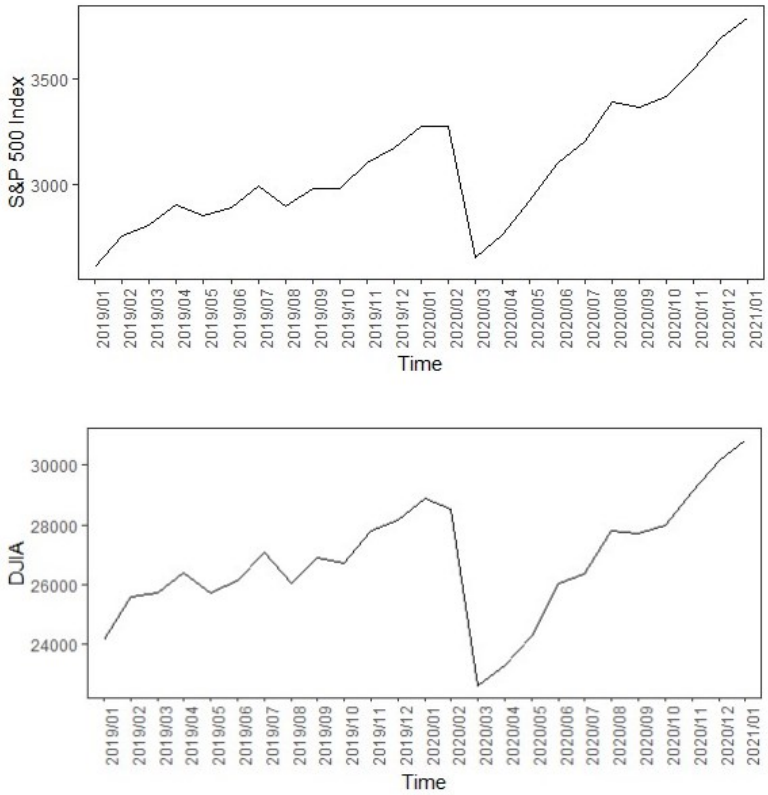

Chart 4 The development of the stock indices.

The pandemic has had varying effects on the different indicators included in the current study. The effects depend mainly on what the indicators measure and how the outcome has been affected by the stock market, Covid 19, and regulations made to lessen the spread of Covid-19. Whether it is production, consumption, sentiment, or other measurable factors, the indicators have had one thing in common: the indicators' values fell during the times of the stock market crash. However, the stock market crash may have only been an onset for recession, and other factors may have

affected the indicators more than the crash itself. Government regulations made to combat the spread of Covid-19 have negatively affected different economic sectors and the economy. Walmsley et al. (2020) estimated that the mandatory closure of businesses has negatively affected the GDP and employment in the U.S., mainly due to the reduction of production and indirectly by a loss of demand in labor. This, in turn, has negatively affected other economic sectors. Furthermore, the consumer and consumer spending have been negatively affected by Covid-19. Income and wealth losses, a reduction in aggregate consumer spending, and negative outlooks on the future, especially regarding employment, have influenced the consumer negatively (Goibion et al., 2020). Additionally, del Rio-Chanona et al. (2020) describe that different industries have and will encounter supply and demand shocks during the Covid-19 pandemic. Industries, such as health and food and necessities, have had an increase in supply and demand, while industries such as hotel, restaurant, travel, and transportation have had a decrease in demand. Industries, such as mining, manufacturing, and service, have been more affected by changes in the supply (del Rio-Chanona et al., 2020).

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5.1 Discussion: Results

5.1.1 Survey-based Indicators

The general objective of the PMIs is to observe and gauge how economic activity in different industries develops (ISM, n.d.a; ISM, n.d.b; IHS Markit, 2017). The questionnaires are sent to many companies operating in the manufacturing and service industries, covering many questions on different economic factors affecting the industry. Therefore, it can be argued that the PMIs could reflect companies' economic activities more clearly, than indicators that measure a single economic factor, such as inflation. However, this could also be interpreted the other way, that is, the PMIs could offer a too narrow view of the economy, especially to be able to effectively be used in the prediction of the development of the stock market indices.

The PMIs in the current study have shown mixed results depending on the performed analytical method. The indicators' correlations with the stock indices (Table 4)

present mostly positive, but also negative correlations. The Chicago PMI displays negative correlations for both stock indices, while the other PMIs show positive correlations for both stock indices. The reason may be that the Chicago PMI measures economic activity in the Chicago area, in which the regional perspective is not large enough in reflecting the development of the S&P 500 index or the DJIA index.

The cross-correlations (Tables -5 and 6) show similar findings for all the PMIs, that is, the highest correlation values emerge when the PMIs are lagged by one month. The PMIs' cross-correlations are in line with the findings of Dovolil (2016). The indicators' correlation and correlation significance (Table 7) display high correlation significance values for all the PMIs except for the Chicago PMI. The reason can be argued to be the same as in the findings of the indicators' correlations with the stock indices. That is, the Chicago PMI measures economic activity in the Chicago area, and the regional view is too minor in comparison to indicators that measure aggregate economic factors of the whole country. The same reasoning can be applied to why the other PMIs have higher correlation significance values with other indicators. That is, they cover more companies operating nationally, which are therefore affected more by aggregate economic factors.

Furthermore, the indicators' correlation and correlations significance (Table.7) led to that all the PMIs, except the Chicago PMI, were excluded from the multiple linear regression models. It was somewhat excepted, due to that the PMIs have been observed to correlate with other indicators, such as the IPI and the PPI (Jeon & Ji-Hong, 2017). Additionally, the PMIs positively correlated with each other and with other indicators, such as the CLI, clarifying that the PMIs are affected by the development of other indicators and that the PMIs also affect other indicators' development. In conclusion, the PMIs might fit better for analyzing other economic factors than the stock indices.

Performing the simple linear regressions with coincidental times (Tables -8 and 9) did not show any meaningful results. However, the simple linear regressions with lagged independent variables (Tables -10 and 11) show significant results for all the PMIs. Previous studies have concluded that the PMIs significantly affect and have a positive relationship with the stock market through studying the effect the PMIs have

on stock returns and stock market index futures (Johnson & Watson, 2011; Hu et al., 2017). In the current study, the relationship between the stock market and the PMIs has been further elaborated through the stock indices' closing prices and the PMIs. However, in the current study, the relationship was only observed when the PMIs were lagged, which is in line with Dovolil's (2016) research.

The PMIs showed a slightly negative development in the indicator's values during 2019 (see Chart 5). This is contrary to the development of the two stock indices during 2019, which continued to rise throughout the year. The IHS Markit PMI and the ISM Non-Manufacturing PMI continued to remain above the level of 50 during the year, while the ISM Manufacturing PMI and the Chicago PMI fell below 50. The Chicago PMI had the largest fluctuations compared with other PMIs, while the IHS Markit PMI had the most neutral development hovering above 50. All the PMIs fell after the stock market crash and after the U.S. government implemented regulations. The values fell as low as 35, showing that the companies answering the survey had highly negative outlooks on the future. This continued for a few months, but the values rose quickly and had somewhat similar developments afterward during 2020. However, the ISM Non-Manufacturing PMI continued to stay around 55 after the stock market crash. The indicator values imply that the companies operating in the service sector had more negative outlooks on the future and may have been more affected by the regulations and restrictions. It can be argued that the PMIs developments are more in line with the recession than they are with the stock market crash, due to the values started already to fall during January and February of 2020, and the NBER stated that the U.S. economy entered a recession in February 2020 (NBER, n.d.).

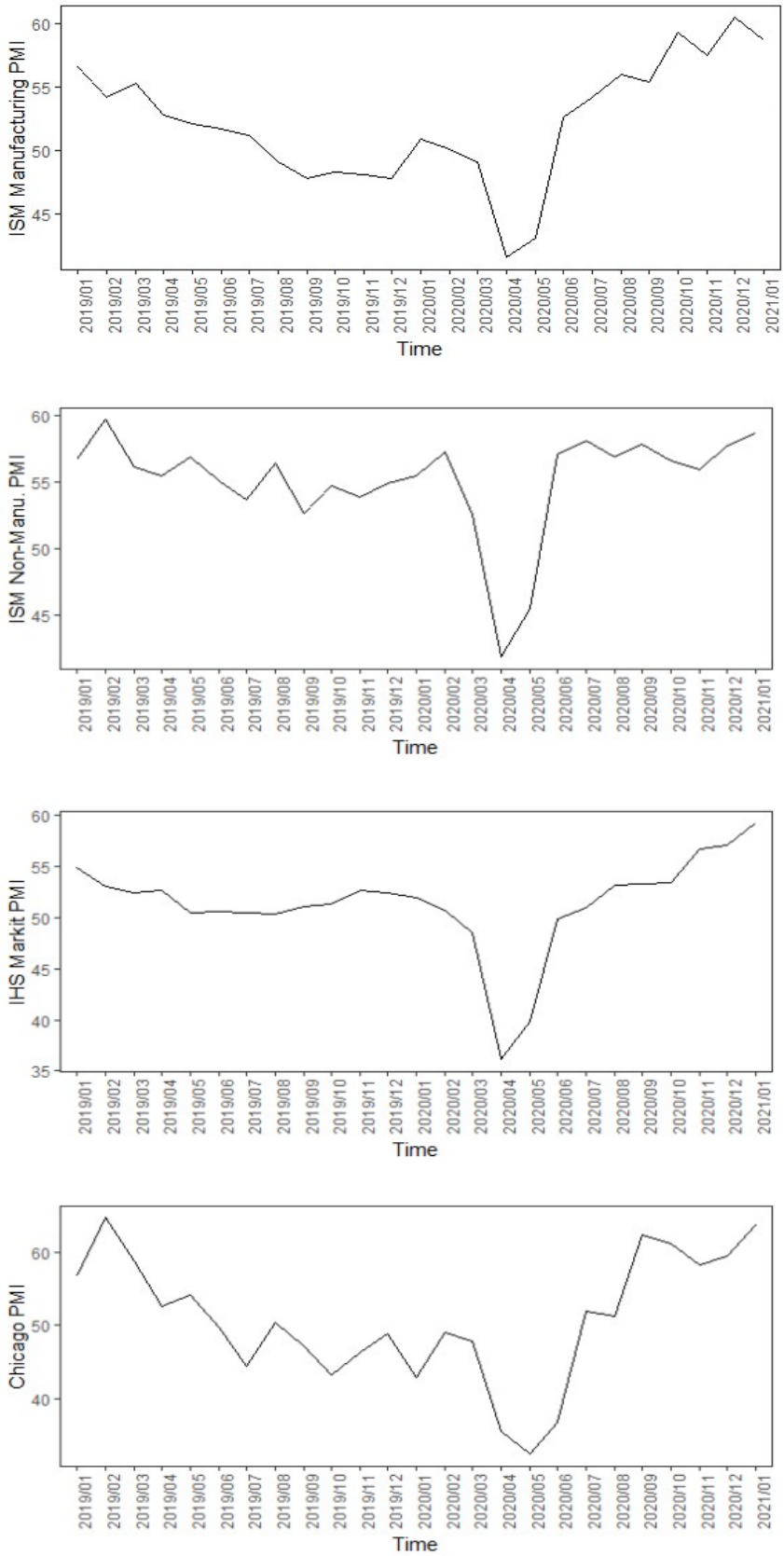

Chart 5 The development of the PMIs.

The CSI shows positive correlations with the stock market indices (Table 4) and relatively high positive correlation and correlation significance values with the other indicators (Table 5). However, the correlations are minor enough for the CSI to be included in the multiple linear regression models. The cross-correlations (Tables -6 and 7) show that the highest correlations are observed for the CSI when the indicator is lagged by one month (t+1).

The CSI was the only indicator that showed a significant result in the simple linear regression with the DJIA as a dependent variable (Table 8). It also showed a minor significant effect on the DJIA in the multiple linear regression model (Table 13). However, the explanatory power of the model was still insignificant. The CSI showed significant results on the DJIA and S&P 500 index while lagged in both the simple linear regression models and the multiple linear regression models, solidifying that the indicator was lagging the stock indices in the current study. Christ and Bremmer (2003) argued that consumer sentiment and the stock market display a short-run relationship, in which consumer sentiment follows the fluctuations of the stock market. These similarities can be drawn with the current study; however, other factors have played a major role in the development of the CSI.

Consumer sentiment fell during the stock market crash of March 2020, and it did not recover to the previous values before the crash, as many other indicators did. This can be linked with the negative expectations consumers had for their personal economy due to Covid-19. Consumers were not only affected by negative expectations on the future but by lockdowns, business closures, and loss in employment, eventually leading to a decrease in consumer spending (Goibion et al., 2020; Walmsley et al., 2020). Additionally, stock market crashes and negative economic news increase consumers' uncertainty and decreases consumer' expectations (Van Dale et al., 2017).

Many factors can be argued to affect consumer sentiment during Covid-19, one of them being the stock market crash. The stock market crash may have been one of the first factors to which consumers reacted, leading to the initial fall of consumer sentiment. This would be in line with Otoo's (1999) observation that the consumer uses the stock market fluctuations as an indicator for future economic development.

However, the difficulties faced by the U.S. economy and the difficulties related to the personal economies of consumers continued to be influenced during the pandemic, leading to low consumer sentiment values continuously, especially when the virus spread, affecting more people and more industries, leading to negative job prospects and uncertainty in the people's future wellbeing.

Interestingly, the CSI is the only indicator in the current study fully concentrating on the consumer, and it shows a drastic development during the Covid-19 pandemic. The consumer can be argued to be more affected by Covid-19 and government regulations than by the stock market crash. The argument is strengthened by that the indicator continued to report low values after the stock market indices had already risen.

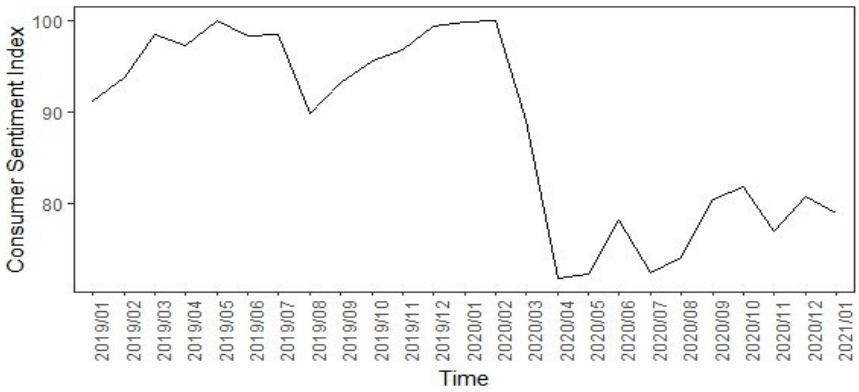

Chart 6 The development of the CSI.

5.1.2 Macroeconomic Indicators

The macroeconomic indicators included in the current study consisted of two indicators concentrating on inflation (CPI and PPI) and one on production (IPI). The discussion of the results of macroeconomic indicators is also performed by following this division.

Macroeconomic indicators and their relationship and effect on the stock market have been extensively researched, through asset pricing theories and as individual variables affecting the stock market and stock returns. One of the often-researched

macroeconomic indicators is industrial production (Rapach et al., 2005; Chen et al., 1986; Serfling &Miljkovic, 2011; Humpe & Macmillan, 2007). However, the use of either the CPI or PPI as variables measuring inflation is also common.

The macroeconomic indicators included in the current study have shown positive correlations with the S&P 500 index and the DJIA (Table 4). It is somewhat unexpected that the PPI and CPI showed positive correlations with the stock indices, due to that in earlier studies, inflation has often negatively affected the stock market (Humpe & Macmillan, 2007; Flannery & Protopapadakis, 2002; Sirucek, 2012; Suk Joong et al., 2014). A rise in the indicators' values have often led to that the stock returns and stock market valuation have fallen, due to that, inflation diminishes the purchasing power.

The cross-correlations (Tables -6 and 7) show that both indicators are lagging the stock indices by one month (t+1). Interestingly, Serfling and Milkovic (2011) demonstrated that historical values of the CPI, together with other variables, could be used in predicting changes in the S&P 500 index. However, the results from the current study could not replicate the results of Serfling and Milkovic (2011). Another difference to the study made by Serfling & Miljkovic (2011) is that the CPI in the current study had too high correlation and correlation significance values with the other indicators, leading to it being excluded from the multiple linear regression models. However, the PPI was included in the multiple linear regression models, showing a significant effect on both stock indices when lagged. The results of the PPI and CPI in the current study are also different from the results of Sirucek's (2012) study. In Sirucek's (2012) study, the PPI had a more significant relationship with the DJIA than with the S&P 500 index when no such results were observed in the current study.

In conclusion, the cross-correlations showed the highest correlation values at t+1, implying that the two indicators have lagging abilities. This was confirmed by the results from the simple linear regressions and from the results of the multiple linear regression models, showing that the indicators were unreliable to be used in the prediction of the stock market indices during the time period of January 2019 to January 2021.

Interestingly, the CPI and the PPI measured a decrease in values during the stock market crash of 2020 (see Chart 7). Furthermore, the values of the PPI fell more than the values of the CPI, followed by a sharp increase in the values. This implies that there was a larger change in the selling prices of producers than the change in prices paid by the consumers. The PPI values also rose faster and to higher levels than the CPI. Furthermore, the rise could be linked with short-term inflation. If the rise would continue, then long-term inflation could occur, which would eventually affect the stock market prices and returns of the market portfolio (Flannery & Protopapadakis, 2002). The reasons for the fall of the PPI and CPI can be partly explained by government regulations and lockdowns. For instance, there was a reduction in demand for hotels and restaurants, and the hospitality industry, resulting in a fall in PPI values (Mendez-Carbajo, 2021). The rise of the values can be credited to the normalization of many industries that had been affected by Covid-19.

Industrial production has been shown to influence stock market development, stock market prices, and stock returns (Sirucek, 2012; Humpe & Macmillan, 2002; Rahman et al., 2009; Rapach et al., 2005). In the current study, the IPI had shown to follow the development of the stock indices, in other words, the development of the IPI can be partly explained by the development of the stock indices. The cross-correlations (see Tables- 6 and 7) show that the IPI had the highest positive correlation values with the S&P 500 index and the DJIA when lagged (t+1). In other words, the indicator values followed the stock indices by one month.

The IPI was excluded from the multiple regression models due to it having high correlation significance values with almost all the other indicators. This was somewhat expected due to that industrial production has been demonstrated to be strongly linked with other macroeconomic indicators. Additionally, changes in other indicators have been described to be able to be used in predicting values of the IPI (Serfling & Miljkovic, 2011). The IPI is also strongly linked with the PMIs due to it measuring changes in the manufacturing industries.

The notion that the IPI follows the stock indices by (t+1) was strengthened when it showed insignificant results in the simple linear regression models (see Tables -8 and 9). Additionally, by showing significant results in the simple linear regressions with

lagged indicators (Tables -10 and 11), concluded that the indicator has been lagging the development of the stock indices during Covid-19.

The fall in the indicator values of the IPI during 2019 was short-lived (see Chart 7). The decrease in industrial output can be mainly argued to be caused by the lockdowns and business restrictions that started in the first quarter of 2020 (Dunford et al., 2020). However, the values of IPI rose rapidly after the lockdowns and regulations were implemented, showing a fast adaptation in manufacturing, mining and gas and electric utility companies to the changes the regulations had. In other words, the connection between the fall of the indicator values and the stock market crash can be argued to be negligible.

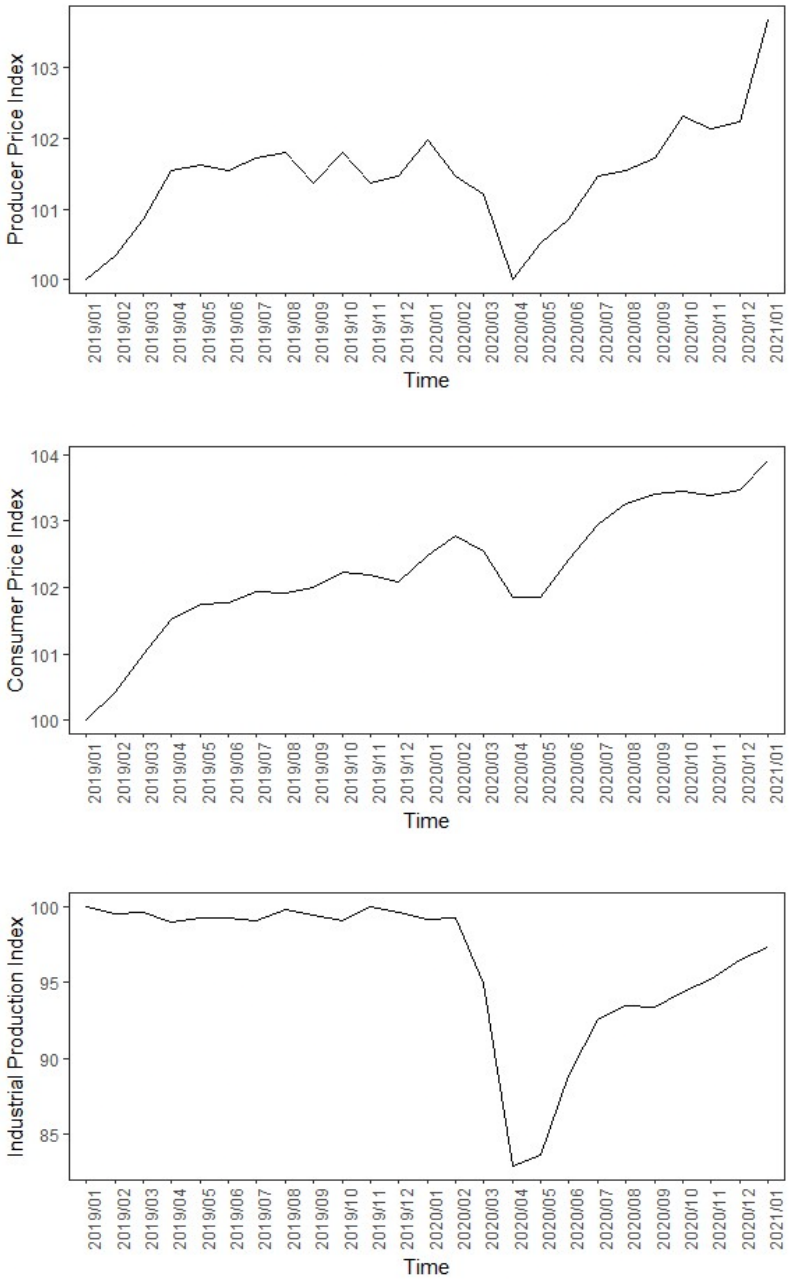

Chart 7 The development of the macroeconomic indicators.

5.1.3 Business Cycle Indicator- CLI

The OECD CLI's objective is to measure and anticipate the turning points of the business cycle (OECD, 2021). The indicator measured the latest trough in the business cycle to have occurred in May 2020 (OECD CLI: Turning Points of

Refence Series and Component Series, 2021). The indicator shows positive correlations with the S&P 500 index and the DJIA index (see Table 4) and high correlation and correlation significance values with the other indicators (Table 5). The high correlations with other indicators can be explained by that the components of the CLI are related to the other indicators (for instance: manufacturing-industrial confidence, weekly hours worked in manufacturing, consumer confidence and share prices of the NYSE composite, OECD CLI: Turning Points of Reference Series and Component Series, 2021). High correlations were observed with the IPI the PMIs, which led to the exclusion of the CLI in the multiple regression models.

The high correlations with other indicators can also be argued to be linked with the phase of the business cycle. An expansion in the business cycle is connected with economic growth, and a downturn in the business cycle is connected with shrinking economic activity (Zarnowitz, 1991). For instance, the high correlation with the IPI shows the connection between the growth in manufacturing industries and the business cycle.

The CLI's cross-correlations with the S&P 500 index and the DJIA (see Tables- 6 and 7) show that it is lagging the stock indices with one month. Furthermore, the lagged CLI in the simple linear regression model shows a significant effect on the stock indices, when performing the simple linear regression with coincidental times show insignificant effects. The results are in line with the results from Celebi and Hönig (2019).

Another connection with results from previous studies can be observed. Dzikevičius and Vetrov (2011) describe that the stage of the business cycle affects the stock market, and the risks and returns. Furthermore, the shrinking of the business cycle negatively affects the stock market. The NBER determined that the recent peak in the business cycle occurred in February 2020 (NBER, n.d.), in which afterward the business cycle started to shrink, reaching the trough in May 2020. The CLI started to report lower values in February 2020 (see Chart 8), showing some indication that the stock indices' values might fall, but the stock market crash was short-lived, and the downturn for the whole economy lasted longer. One may argue that this made the indicator unreliable to be used in relation to predict the stock market development.

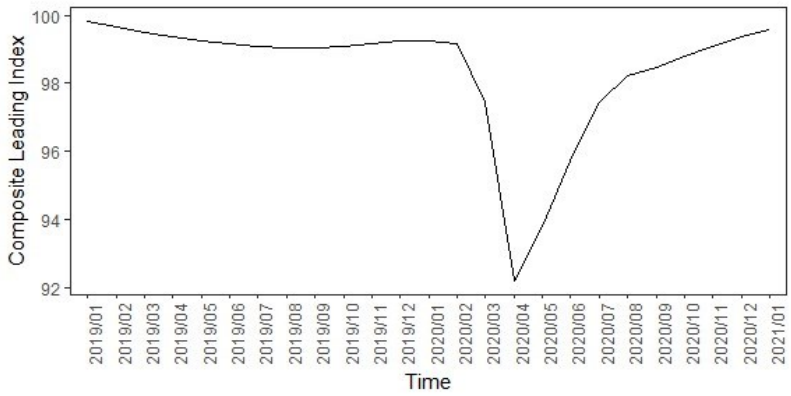

Chart 8 The development of the CLI.

5.2 Limitations

During the conduction of the current study, Covid-19 was still ongoing, and all the effects that it had on the stock market, indicators, and the economy were still unknown. Therefore, the current study was unachievable to describe all the factors that influenced the indicators and the stock market.

This study was conducted using the time frame of January 2019 to January 2021. To observe and describe the full effects of Covid-19 had on the indicator's performance in relation to the stock market, a longer time frame would have been preferable. This would have made the analyses more accurate in observing the effects of Covid-19 and in assessing how well the indicators performed in relation to the stock market. A longer time frame would have also made it possible to divide the time frame into periods: before, during, and after Covid-19, making it possible to make comparisons on how well the indicators have performed.

Additionally, analyzing monthly data instead of daily data has its own shortcomings when using a short time frame. All the changes in the stock market and indicators cannot be fully perceived. This, in turn, makes the findings from the analyses not as detailed as the possible findings from using daily data.

It could be argued that more comparable indicators and stock market indices should have been used in the study. For instance, studying indicators that measure economic activity in certain industries and then choosing stock market companies that operate in these industries could have led to more reliable results. There are also other

possible approaches that could have been used. The number of indicators could be argued to be too few to be able to research the phenomena from enough different perspectives. However, one factor fundamentally limiting the number of indicators was the limited access to the data for different indicators. Many indicators are published by private institutions, limiting the access without having certain credentials or by simply making the access to the indicator data cost.

There are sophisticated analytical methods that could have better explained the relationship between the indicators and the stock market indices. Additionally, describing the effects of Covid-19 on the indicators and stock market indices. The analytical methods included in the study were of familiar use to the author and provided essential information about the relationships between the variables, ultimately leading to their use in the current study.

6. Conclusion

The main aim of the study was to understand how the indicators can explain the variation of the stock market indices' values and how they have been affected by Covid-19. The time period for the data of the indicators ranged from January 2019 to January 2021. Nine indicators and two stock market indices were included in the study. The indicators were divided into different categories, determined by what and how they measure economic activity. Further, the indicators were compared by other similar ones. Additionally, the indicators were analyzed in relation to the stock market indices, that is, if they display leading, coincident, or lagging information in relation to the stock market indices.

To understand the context of the present study, that is, how the stock market has developed during the pandemic, and how the indicators have been affected by Covid-19, theory related to business cycles and the stock market was presented. Additionally, why, and how the business cycle fluctuates and how the stock market and business cycles are connected were described. Further, stock market development theories, such as the random walk hypothesis and efficient market hypothesis were presented. Furthermore, asset pricing models, such as the capital asset pricing model and its extensions and the arbitrage pricing theory were described. The indicators were also thoroughly described, and the results of previous research in which the indicators were studied in relation to the stock market were presented.

The current study was conducted as a quantitative study with various analytical methods. However, before the analysis was conducted, minor data processing was performed, including logarithmic transformation and the first difference. Additionally, the performed data processing depended on the indicators' index type. The analysis began by conducting correlations with the indicators and the stock market indices. This was followed by measuring the indicators' correlation and correlation significance. In addition, cross-correlations with the indicators and the two stock market indices were performed. Following the correlation tests, simple linear regressions were conducted with the indicators as independent variables and the stock indices as dependent variables. Further, simple linear regressions that used the lagged values for the indicators from the cross-correlations were conducted.

Multiple linear regression analyses with the indicators with the lowest correlation and lowest correlation significance values with each other were conducted. Lastly, multiple linear regression analyses that used lagged values for the indicators were performed.

The indicators' correlations with the stock market indices were positive, except the correlations of the Chicago PMI. The indicators' correlation and correlation significance resulted in six of the indicators being excluded from the multiple linear regressions. The indicators that were included for the multiple linear regressions were the following: CSI, PPI, and Chicago PMI.

The results from the cross-correlations show that the indicators' highest correlation values with the stock market indices occur when lagged by one month (t+1). Furthermore, performing simple linear regression analyses show insignificant results, except for the CSI when the DJIA was the dependent variable. However, performing the simple linear regressions with lagged independent variables showed significant results for all the indicators. Additionally, similar results were observed when performing the multiple linear regression analyses. That is, insignificant results when performing the multiple linear regressions with coincidental times for the indicators and stock indices, and significant results when performing the multiple linear regressions with lagged values for the indicators.

The results from the analyses indicate that the indicators from January 2019 to January 2021 were lagging the stock market indices. In other words, the fluctuations of the stock market indices precede the movement of the indicators. From this can be concluded, that the indicators could not be reliably used to predict the stock market from January 2019 to January 2021 or the stock market crash of March 2020. In addition, the indicators' values developed differently after the stock market crash, depending on how the measured activity had been affected by Covid-19. For indicators in the survey-based category, most of the PMIs returned to similar levels as before the stock market crash, while the CSI continued to stay on a lower level than before the crash. It can be argued that Covid-19 and government regulations have affected the consumer more than it has the manufacturing or service sectors, leading to a decrease in consumption. The macroeconomic indicators except for IPI, in turn, have risen above the previous levels before the stock market crash. The PPI

and CPI have risen sharply, leading to concerns of short-term inflation. The possibility of long-term inflation was unknown during the making of this study. The business cycle indicator, OECD CLI, had started to report lower values after the business cycle peak of February 2020 (NBER, n.d.). However, the indicator was unable to predict the fluctuations of the stock market indices fully.

In conclusion, the indicators could not reliably explain the developments of the stock indices during the time period of January 2019 to January 2021. Many factors, directly and indirectly, affected the development of the indicators and the stock indices, mainly effects of regulations the U.S. government implemented to combat Covid-19.

The current study has made a preliminary description of the indicator's performance during Covid-19. This study's results could help in explaining what factors have affected the indicators, and how the indicators' relationship with the stock market has developed during Covid-19. The findings of this study are essential in understanding how the indicators can be used by market participants in analyzing stock market development.

6.1 Future Research

The results from the current study and the results from earlier studies show that the indicators have performed varyingly depending on the country and time frame used in the studies. Furthermore, there are other factors that affect the indicators and the stock market. For instance, an economy that continues to change and globalize and rapidly developing technology that affects different economic sectors may ultimately lead to different results in future research. Therefore, concentrating on a single indicator by observing a longer time frame could be preferable. This way, all the factors affecting the indicator and the phenomena behind them could be thoroughly researched. Additionally, any changes in the indicator's construction method could be observed.

Regarding the current study, how well the indicators have performed in relation to the stock market during the Covid-19 pandemic is still unknown. The implications of

what Covid-19 have had on the stock market and indicators can only be completely understood in the future when the pandemic is over.

Future research could concentrate on researching fewer companies listed on the stock market or perform the research as a case study. Research could concentrate on companies that operate in a specific industry and select the corresponding indicators measuring economic activity in that industry. For instance, selecting to research a manufacturing company could narrow down the selection of indicators and show more concrete results. This would also make it easier to understand the reasons why and how the company's stock market value fluctuates.

Swedish Summary - Svensk Sammanfattning

Covid-19, Indikatorer och Aktiemarknaden – Utvärdering av Indikationer i förhållande till Aktiemarknaden under Coronapandemin

Inledning

Coronapandemin har orsakat mycket fluktuationer och osäkerhet på den amerikanska aktiemarknaden. En av de största följderna som pandemin fört med sig är kraschen av aktiemarknaden i mars 2020. Kraschen som blev en början för recession i USA (The National Bureau of Economic Research, n.d.).

Aktörer på aktiemarknaden kan använda sig av olika redskap för att underlätta agerandet på aktiemarknaden. Redskapen stöder aktörerna i deras beslut om att delta i aktiemarknaden. Ekonomiska och finansiella indikatorer är exempel på den här typen av redskap. Indikatorerna kan vara till nytta för att försöka förutspå hur aktiemarknaden fluktuerar och hur värdet på aktiemarknadsindex utformas. Indikatorerna kan indelas i grupper beroende på typen av information de ger, till exempel om produktion och konsumtion, och det ändamål som de kan användas till. Indikatorerna visar information som kan användas för att förstå förfluten, aktuell och framtida utveckling av aktiemarknaden.

Vilka indikatorer och hur bra de har mätt utvecklingen av aktiemarknaden har varierat under olika recessioner (Stock & Watson, 2003). Det finns även variation i hur väl indikatorerna har presterat under olika tidsperioder och i olika länder (Rapach et.al, 2005). Sammanfattningsvis kan det påstås att vissa indikatorer har varit inkonsekventa, medan andra har presterat bättre i flera studier. Ett exempel på detta är konsumentprisindexet. Konsumentprisindexet har både rapporteras ha en icke-signifikant effekt på S&P 500 indexet (Hamid et.al, 2006) och en signifikant effekt då den har studerats tillsammans med flera variabler (Serfling & Miljkovic, 2011). Charoenrook (2007) har kommit fram till att konsumentens sentimentindex (eng. *Consumer sentiment index,* egen översättning) kan användas till att förutspå aktiemarknadens avkastning (Charoenrook, 2003). Christ och Bremmer (2003) hävdar i sin tur att aktiemarknaden påverkade indikatorn, men att indikatorn i sig inte hade någon effekt på aktiemarknaden.

Industriproduktionsindexet verkar vara en av de indikatorer som har presterat bättre. Tidigare forskning tyder på att den påverkar aktiemarknaden signifikant (Humpe & Macmillan, 2007; Serfling & Miljokovic, 2011; Rahman et.al, 2009). Ytterligare har en del indikatorer också visats kunna förklara variationen i aktiemarknaden bättre då de har förvandlats till tidsförskjutna variabler (Celebi & Hönig, 2019).

Syfte och ämnesmotivering

Syftet med denna avhandling var att tydliggöra hur olika indikatorer kan användas för att förutspå aktiemarknaden. För detta ändamål har nio indikatorer valts. I avhandlingen inkluderades÷ OECD:s sammansatta ledande indikatorer (eng. *Composite Leading Indicator*, egen översättning), ISM produktionsinköparindex (eng. *ISM Manufacturing PMI,* egen översättning), ISM tjänsteinköparindex (eng. *ISM Service PMI*, egen översättning), IHS Markit inköparindex (eng. *IHS Markit PMI*), Chicago inköparindex (eng. *Chicago PMI*), producentprisindex, konsumentprisindex, konsumentens sentimentindex (eng. *Consumer sentiment index*, egen översättning) och industriproduktionsindex. Aktiemarknaden representerades av S&P 500 index och DJIA index.

Huvudsyftet med avhandlingen var att undersöka hur indikatorerna fungerat under coronapandemin i relation till utvecklingen av den amerikanska aktiemarknaden och om de kan användas till att förutspå dess utveckling. Vidare var syftet att få förståelse för hur väl indikatorerna kan användas i olika sammansättningar, det vill säga om utvecklingen kunde förstås bättre genom att använda en eller flera indikatorer. Dessutom jämfördes liknande indikatorer med varandra för att se vilka av dem fungerar bäst.

Orsaken till att studien utfördes var att utreda om indikatorerna kan användas av deltagare på aktiemarknaden och beslutsfattare i olika organisationer. Att kartlägga olika indikatorers prestationer i relation till aktiemarknadens utveckling är viktigt för att det hjälper aktörer på aktiemarknaden att avgöra vilka indikatorer det lönar sig följa och använda innan de fattar ett investeringsbeslut. Ytterligare är studien aktuell och ger värdefull information om coronapandemins effekter på ekonomin.

Metod och redogörelse för undersökningen

Avhandlingen följer en kvantitativ forskningsmetod. Indikatorerna inkluderades i avhandlingen baserat på bland annat följande inklusionskriterier: de måste mäta amerikansk ekonomisk aktivitet, de måste vara publicerade av välkända institutioner eller organisationer och det måste finnas tidigare forskning om dem i relation till aktiemarknaden.

För att besvara forskningsfrågorna begränsades datainsamlingen till tidsperioden från januari 2019 till januari 2021. Indikatorerna var oberoende variablerna i avhandlingen, medan aktiemarknadsindexen var beroende variablerna.

D första analyserna som utfördes var korrelationer mellan aktieindexen och indikatorerna. Styrkan av associationerna mellan indikatorerna och aktieindexen prövades. Sedan analyserades korrelationer och signifikansen av korrelationerna bland indikatorerna. Korrelationerna och de signifikanta resultaten av dessa avgjorde vilka indikatorer som kunde användas i en senare multipel regression. För att förstå sambandet mellan indikatorerna och aktieindexen gjordes korskorrelationer. Korskorrelationerna i sin tur förklarar hur indikatorerna och indexen förhåller sig till varandra. Resultaten från korskorrelationerna användes senare i en enkel lineär regression och i en multipel regression där de oberoende variablerna var tidsförskjutna. Enkla lineära regressioner och enkla lineära regressioner med tidsförskjutna variabler gjordes med alla variabler. Multipla regressioner utfördes för att kartlägga relationen och signifikansen av indikatorerna och aktieindexen. Analyserna gjordes i programmet R(ref).

Resultat

Alla de indikatorer som inkluderats i denna avhandling förutom Chicago inköparindexet hade en positiv korrelation med S&P 500 indexet och DJIA indexet. Korrelationerna och korrelationssignifikanserna bland indikatorerna antydde att Chicago inköparindexet, konsumentens sentimentindex och producentprisindexet uppfyllde kraven för att inkluderas i de multipla regressionerna. Övriga indikatorer hade för starka korrelationer och korrelationssignifikanser för att multikollinearitet skulle ha kunnat uteslutas. Resultaten från korskorrelationerna för både DJIA indexet

och S&P500 indexet visade att alla indikatorer släpar efter aktieindexen med en månad. Resultaten från de enkla lineära regressionerna var icke-signifikanta. Resultaten från de enkla lineära regressionerna med tidsförskjutna variabler var däremot signifikanta för varje indikator. Ytterligare var resultaten från den multipla regressionen icke-signifikanta. Resultaten från de multipla regressionerna med tidsförskjutna variabler var signifikanta för varje indikator.

Diskussion och avslutning

Avhandlingen fokuserade på ett aktuellt tema, det vill säga på att utvärdera hur väl indikatorerna fungerat under coronapandemin. Avhandlingen har gett en inblick i detta. Resultaten från tidigare forskning har kunnat konstatera att det finns mycket variation i hur indikatorerna har presterat. Resultaten från denna avhandling kan i stort sägas gå i linje med tidigare studiers resultat. Dock fanns det ett par undantag. I denna avhandling hade Industriproduktionsindexet endast en effekt på aktieindexen då indikatorn varit tidsförskjuten, medan tidigare forskning rapporterat att den alltid haft en signifikant effekt oberoende om den var tidsförskjuten eller inte (Humpe & Macmillan,2007; Serfling & Miljokovic, 2011; Rahman et.al, 2009). Resultaten för Producentprisindexet och Konsumentprisindexet påverkade aktiemarknadsindexen enbart då de var tidsförskjutna, vilket skiljer sig från vad tidigare forskning konstaterat (Hamid et.al, (2006).

Det är värt att notera att det i denna studie uppstod signifikanta resultat för varje indikator då de var tidsförskjutna, vilket är i linje med resultaten av Celebi och Hönig (2019). Detta kunde tyda på att då man tidsförskjuter variabler ökar det signifikansen. Utgående från detta kan det konstateras att indikatorerna följer utvecklingen i aktiemarknaden och efter att förändringen i aktiemarknaden har skett förändras även värden i indikatorerna.

Det finns faktorer som påverkar hur bra indikatorer går att använda i relation med aktiemarknadens utveckling, vilket även denna avhandling ger stöd för. Tidsperioden som man väljer för analyserna spelar en stor roll, ju längre tidsperiod desto tydligare svar kan man förvänta sig. Det finns dock också problem med att välja en alltför lång tidsperiod. Indikatorerna kan utvecklas och flera variabler kan läggas till i dem, vilket försvårar användningen av indikatorerna under en längre tidsperiod och kan

även förändra dess prestation. Det bör även noteras att aktiemarknaden också förändrats under en längre tidsperiod och att varje recession kan orsaka förändringar i ekonomin, vilket kan påverka hur aktierna har presterat före och efter ekonomiska kriser. Dessutom utvecklas den globala ekonomin hela tiden. Multinationella företag verkar i olika länder och då ekonomiska kriser sker i ett land kan det antingen påverka andra länder eller inte. Ju mer ekonomin globaliseras desto mer globaliseras också enskilda länders aktiemarknader.

Framtida undersökningar skulle kunna koncentrera sig på färre indikatorer och använda mera avancerade analysmodeller för att få tydligare svar. Uttömmande analyser om indikatorer och aktieindex skulle kunna vara något som kunde utföras i framtida studier. De inkonsekventa resultaten tyder på behovet av ytterligare forskning.

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