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Can the stock market predict changes in macroeconomic variables?

Bachelor thesis

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Abstract

There is a consensus in the literature, that the stock market can predict the Gross domestic product on quarterly base or the industrial production, which is good proxy for GDP, on monthly basis and that the causal relationship between stock market and GDP should work both ways. However, using Vector autoregression model on US data since 1950, model shows that the stock market can not only predict the Industrial production on monthly basis, but also ISM non-manufacturing index, which is a good proxy for services in the economy. Furthermore I have managed to prove, that the unemployment can be predicted by past realizations of the stock market and managed to explain almost one third of all variations in change in unemployment using S&P500 and oil prices during last 20 years. The Granger causality test concluded that stock market does cause the unemployment but not vice versa, at least during last 20 years.

Keywords

Stock market, Macroeconomic variables, Vector autoregression, Granger causality test, Unemployment, GDP, ISM non-manufacturing index

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Abstrakt

V odborné literatuře existuje konsensus, že akciový trh může předvídat hrubý domácí produkt na čtvrtletní bázi a průmyslovou výrobu, která se často používá při odhadováni HDP, na měsíční bázi, a také že kauzální vztahy mezi akciovým trhem a HDP by měly fungovat oběma směry. Použitím vektorové autoregrese na amerických datech od roku 1950 ukazuji, že akciový trh může nejen předvídat průmyslovou výrobu na měsíční bázi, ale také ISM non-manufacturing index, který slouží jako dobrý odhad pro služby v ekonomice. Dále se mi podařilo prokázat, že nezaměstnanost může být předvídaná minulými realizacemi akciového trhu a podařilo se mi vysvětlit téměř třetinu všech změn ve nezaměstnanosti pomocí S&P500 a ceny ropy během posledních 20 let. Grangerův kauzální test ukázal, že akciový trh způsobuje nezaměstnanost, ale ne naopak, přinejmenším během posledních 20 let.

Klíčová slova

Akciový trh, Makroekonomické ukazovatele, Vektorová autoregrese, Grangerův test kauzality, Nezaměstnanost, HDP, ISM non-manufacturing index

Declaration of Authorship

I hereby proclaim that I wrote my bachelor thesis on my own under the leadership of my supervisor and that the references include all resources and literature I have used.

I also declare that this thesis was not used for obtaining another degree.

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Prague, 8 May 2017

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Acronyms

GDP	Gross domestic production
US	United states of America
IP	Industrial production
VAR	Vector autoregression model
p	number of lags used in the Vector autoregression model
BLS	Bureau of Labor Statistics
CPI	Consumer price index
OECD	The Organisation for Economic Co-operation and Development
FED	Federal Reserve
HQC	Hanna-Quinn information criterion
AIC	Akaike information criterion
SC	Schwartz information criterion
KPSS	Kwiatkowski Phillips Schmidt Shin

Bachelor Thesis Proposal

Author	Marek Vařeka
Supervisor	doc. PhDr. Ladislav Krištoufek, Ph.D.
Proposed topic	Can the stock market predict changes in macroeconomic variables?

Preliminary scope of work

Since 1930s when The Great Depression occurred, many economists have wondered if it were possible to achieve sustainable growth and if it were possible to predict and avoid crisis. Many of them thought that the Neoclassical theory was the solution. In the last decade, there has been the biggest crisis since the Great Depression. The neoclassical theory failed to predict that crisis. Since then, many economists have wondered what could have been done differently. It is believed that stock market can give us the solution. In stock market, there is knowledge of all participants reflected into prices. There have been many papers on how macroeconomic variables can predict fluctuations on the stock market. But the macroeconomic indicators are usually known with a relatively big delay. In contrast, stock markets react almost immediately. That is why I have decided to further study stock market and focus on its interconnection with macroeconomic variables, specifically whether the movements in the stock markets precede the movements in macroeconomic variables.

The main contribution of my work should lie in answering several questions that have not been answered. Also there is a possibility I will be able to predict future recessions. It can be helpful for governments to know in advance what is happening and act upon it.

Regression analysis of stock market indices (S&P500, commodity prices and industrial averages) data will be used to predict the Macroeconomic variables. I will use data from data from Yahoo finance and apply knowledge from Econometric classes.

Outline

1. Introduction
2. Motivation
3. Stock market
4. Methodology
5. The data and regression
6. Discussion
7. Conclusion
8. Appendix

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Contents

Introduction

"The stock market has predicted nine of the last five recessions!"
(Samuelson and Nordhaus, 2010)

Causal relationship between the stock market and macroeconomic variables is a relevant topic of the modern economics. The recent financial crisis in 2008 has stimulated research in this field,[1] in order to find possible tools to prevent such an economic phenomenon. Wall Street bankers and deal makers, the Federal Reserve, the government, even the economists failed to fully understand and comprehend potential implications of housing bubble, the main cause of the financial crisis, that has been forming. Colander, Föllmer, Haas, Goldberg, Juselius, Kirman, Lux and Sloth (2009) in their paper criticized academic economists, whom have been unaware of the long build-up to the current worldwide financial crisis. All information, currently available to all participants in the economy, are contained in the stock market, therefore, the stock market should be helpful in predicting future changes in main macroeconomic variables and those information should be useful for Fed and government, to implement monetary and fiscal policy to prevent potential crisis.

The academic literature is more focused on opposite relationship, how to correctly predict stock market using macroeconomic variables (for example paper from Cutler, Poterba and Summers (1988)). Luckily in recent decades some scholars focused on the stock markets and its possibilities to predict gross domestic product. One of the main papers is from Beetsma and Giuliodori (2012) who studied, how the volatility of the stock market affect GDP in the US on the quarterly basis, which can be seen as too slow if we take into consideration how fast the stock market absorbs new information available. Before them, Choi, Hauser and Kopecky (1999) have used stock market to predict the Industrial production, which is good proxy for GDP, on monthly basis. But non of the scholars tried to use services index as a proxy for GDP, while the services account almost for 80% of the GDP (Worldbank, 2017). Moreover, there is no academic paper studying the ef-

[1] See Diebold and Yilimaz (2008)

fect of the stock market on the future unemployment. Boyd, Jagabbatham and Hu (2001) focused on opposite relationship using the unemployment and dummy variable for state of the economy [2] to predict the stock market, but the research can be criticized, because the economic agents do not know the state of the economy at the time of the forecast.

To fill the void of knowledge the Vector autoregressive model, which has been praised as the key empirical tool in modern macroeconomics (Negro, and Schorfheide 2011), will be applied on two hypotheses. The first hypothesis asks, if the stock market can predict proxies for GDP. If the first hypothesis is true, then based on the Okun's law, the stock market should be also able to predict the unemployment, which is the second hypothesis of my thesis.

The thesis is organized as follows: Literature review gives an overview of important literature contributing to relationships between the stock market and macroeconomic variables. In Chapter 2, the stock market and its indexes are introduced and explained. Chapter 3 gives overview of main macroeconomic variables that will be used later in analysis. The methodology of analysis is explained in Chapter 4. In Chapter 5, all transformation of the data is explained. The testing, of two hypothesis introduced in the introduction with VAR model, is done in Chapter 6. Finally, the Conclusion concludes.

[2] This data is published by National bureau of economics reasearch (NBER) but the information is not available in the current month, it usually takes 6 to 21 month to determine peak or trough of the economy.

1 Literature review

Economics is field, where almost every small change can have big consequences on the overall economy. Causal relationships between different variables are often hard to interpret. Economists frequently disagree on interconnections between variables in various fields of economics. The macroeconomics is no difference. The literature concerned with ties between macroeconomic variables and fluctuations in stock market can be divided into two subgroups by causality relations.

On the one hand, the majority of economists are focused on predicting stock market using macroeconomic variables. This approach would have tremendous practical applications if found truthful. One of the earliest work was done by three economists Cutler, Poterba and Summers (1988). They tried to explain variance in stock return, that can be attributed to various macroeconomic news using vector autoregression model during relatively long time period from 1926 to 1985. They managed to explain about one fifth of variations. The relatively small market responses to macroeconomic news accompanied by the fact, that large market fluctuations, which happen on days without any major news cast shadow on ambitions to successfully explain all fluctuations in stock market. Those findings are in line with Schwert (1981) who looked into daily data from S&P500 returns from 1953 to 1978 and found out that stock responses to inflation are weak and slow. Later McQueen, Roley (1990) broadened Cutler's work, adding dummy variable for different states of economy achieving better results, because same news during different states of economy (contraction and expansion) have different impact on stock market. It partly explained very small relevance of the news for the stock market in previous studies. But still only relatively small portion of the fluctuations were predicted, and improved prediction was reached only in the expansion state of the economy. Consequently Boyd, Jagannatham and Hu (2001) focused solely on unemployment and justified why, on the one hand rise of the unemployment is good news for stock market during expansion and bad news during contraction, on the other hand why decline of the unemployment is good news for stock market during contraction and bad news during expansion. To do so they managed to decompose information in unemployment into two parts, the future interest rates and future dividends. If unemployment rises, it translates into decline in interest rates, which is good news for stock market and decline in dividends, which is bad news for stock market. The importance of those two change based on business cycle.

Different approach undertook Cambell, Mei (1993) who decomposed asset's betas (indicators in finance, which indicate level of volatility of certain assets, used in CAPM model) into components that could be attributed to different macroeconomic variables like inflation and industrial production. For analysis they applied vector autoregressive model on time series from 1952 to 1987. Nikkinen, Omran, Sahlstrom and Aijo (2016) decided to do broader view and analyzed how macroeconomic announcements in United States affect Global stock markets around the globe, resulting into conclusion that United state's macroeconomic announcements, are indeed to some extent important for stock markets mostly in European countries, G7 countries and developed Asian countries. Latin America and transition countries were not affected.

Generally, authors were able to predict only small part of the variations of stock market. Part of the fluctuations in stock market can be also attributed to "animal spirits", mass psychology or some unobservable variables. Some economists, for example Kim and Verrecchia (1991 a,b) suspected macroeconomic news are highly anticipated and traders collect private information before public announcement. The prices only change due to unexpected news. Same conclusion was also reached by Roll (1984). He studied fluctuation of orange juice futures determined by changes of weather, the most important determinant of future orange crop. He concluded, that only small fraction of the observed variability can be predicted by changes in weather.

On the other hand, the minority of the economists focused on opposite relationships, how can the stock market predict macroeconomic variables. Camincioli (1995) applied Granger causality test and found out that stock prices do cause economic activity. Later work of Cambell, Lettau, Malkiel and Xu (2001) suggested stock market volatility can predict GDP growth. In same manner continued Mele and Formari (2009) who predicted about one third of post-war economic activity in the US using financial volatility. Furthermore, they found out that the stock markets predicting power has substantively increased during the last 25 years, a period called Great Moderation due to fall in real aggregates volatility. Followed by Choudhry, Papadimitriou and Shabi (2016) who applied both linear and nonlinear causality tests on data from 1990 to 2011 from United States, Canada, United Kingdom and Japan, which resulted in strong evidence of bidirectional causality between stock market volatility and the gross domestic product. Beetsma and Giuliodori (2011) explored changing relationship between the stock market and gross domestic product prior and after 1987. In the first period, fall of S&P500 caused fall in consumption and investment part of Gross domestic product in United States. In the second period, only investment was affected. Milani (2011) took broader perspective and analyzed wealth effect of a larger foreign stock market on small open economies holding high amounts of foreign equity, namely Australia, New Zealand, Austria, Ireland and Netherlands. He concluded that the more foreign equity country hold, the more it is affected by its fluctuations.

To sum it up, both groups of the economists have done a remarkable work to broaden our horizons. The first group managed to partly explain and predict stock market by using macroeconomic variables. The latter group proved stock market can also predict macroeconomic variables and the relationship between stock market and macroeconomic variables can be indeed bi-variate. Those findings imply the usefulness of further studies of the stock market and its implications about the future macroeconomic prospects of the economy.

2 The Stock Market

"Every individual... neither intends to promote the public interest, nor knows how much he is promoting it... he intends only his own security; and by directing that industry in such a manner as its produce may be of the greatest value, he intends only his own gain, and he is in this, as in many other cases, led by an invisible hand to promote an end which was no part of his intention." (Smith, 1863)

The market place can be one of the most marvelous inventions of the man. The Adam Smith's Invisible hand takes all information from buyers and sellers into account. Then, the prices are set in a way so the best allocation of the scarce resources is achieved. The price represents all information from all market actors that are available. The stock market is no different. The Stock exchange is a regulated auction market where stocks, bonds and other securities are bought and sold.

2.1 History of The Stock market

The first stock market with similarities to modern stock markets could be found in France in 12th century, where first French traders managed agricultural debts for banks or in the 13th century in the famous Italian city called Venice, known for its developed banking system, where brokers traded governments bonds (Coispeau, 2017).

The more sophisticated stock markets emerged in the begging of 17th century in the Western Europe. Sailors from Belgium and Netherlands sailed east in the 1600s, to bring goods from the colonies that could be traded back home. But bad weather, pirates and poor navigation skills could cost expedition to lose everything. Ship owners sought investors to fund their voyages to decrease the riskiness of the business in return for part of the profit. Later in 1657 in the United Kingdom, the first joint stock company the East India Company, issued paper stocks and become forerunner of the modern multinational (Robins, 2012). But things happened so quickly that there were no regulations for companies issuing shares. The bubble burst, when the South Seas Company failed to pay dividends due to diminishing profits. A crash followed, and England outlawed shares until 1825.

The London Stock Exchange was officially established in 1801, but due to ”ban on the shares” its functionality was limited. That led to increasing importance of The New York Stock exchange, which made the first corporate stock exchange in 1817 (Gagandeep, 2014).

2.2 The most important Stock markets

The largest Stock market based on market capitalization is the New York Stock Exchange. For many years it relied on open outcry system. More than half of the transaction were transitioned to electronic system, but floor traders are still used in high volume trading.

The second largest stock market is National Association of Securities Dealers Automated Quotations, also know as NASDAQ. The NASDAQ was created in 1971 and was the first electronic stock exchange. The majority of the companies listed on NASDAQ are technology companies like Google, Apple, Tesla motors, etc. Other important stock exchanges are Tokyo stock exchange, London stock exchange or Toronto stock exchange.

2.2.1 The Dow Jones Industrial Average

The oldest stock exchange index is Dow Jones Industrial Average, also know as DJIA, created by Charles Dows. It dates back to 1896 when it was firstly calculated (O'Conor, 2014). DJIA consists of thirty US companies that are selected by special commission. Probably the only advantage of Dow Jones is it's age, therefore, it's popularity.

Many Economists criticize it's way of calculation. The main issue is that Dow takes into account nominal value of the stock, rather than capitalization of whole firm. For example ExxonMobil ,one of the largest companies in history divides its value to nearly 5 billion shares, has less weight in DJ than relatively small Caterpillar, which has small number of shares but more expensive ones. Dow does not adjust for inflation either. It means that same values in DJIA do not tell the same story.

Dow does not represent US economy very well. The companies that compose the index do not change very often. For example Google, one of the most important firms in the world, is not listed in Dow. To the more disturbing matter, it does not make sense of increasingly interconnected global economy, what's good for G.M. isn't always good for the whole country as it used to be in 1950.

2.2.2 The Standard & Poor's 500

The Composite index dates back to 1923, when it was tracking 233 different companies on weekly bases. Back then, when computers still lacked computing power, it was quit hard to manage huge amounts of data on daily basis. Because of that, Poor's Publishing launched parallel index SP&90, which managed to record 90 firms from different sectors, namely 50 industrials, 20 rails, and 20 utilities on daily bases. In 1941, Poor's Publishing merged with Standard Statistics and company S&P was born. Real SP&500 index, as we know it today, was born on on 4th of March 1957 Wilson (2002).

The S&P500 is much larger index than Dow. As it is obvious from its name, it consists of 500 different US companies representing almost 80% of total value of all firms publicly listed in the US. In contrast to Dow, it is capitalization weighted instead of price of stock weighted. It means that bigger companies (with bigger market capitalization) have bigger impact on index than smaller companies with more expensive stocks. The majority of Economists agree that S&P500 is better and more comprehensive index than DJIA.

2.2.3 The Wilshire 5000

The Wilshire 5000 index was created by Wilshire Associates in 1974 with the time series of data beginning on December 1970. Same as the S&P500 it is capitalization weighted. It consists of companies with headquarters in US, whose stocks are traded on American stock exchange. The information about stock pricing is widely available. It is considered as first and the oldest measure of the total US equity. As of today it consists of 3618 companies (Wilshire Associates, 2016).

2.2.4 Other indexes

There are many different stock indexes in United States. The S&P500, Dow and the Wilshire 5000 are the most known and those indexes represent the whole US economy. There are several, indexes which take narrower perspective and focus on specific types of the economy.

One of the most performing index is the Barron's 400 Index. It was developed by MarketGrader and Borron's in September 2007. It consists of the 400 most fundamentally sound and reasonably priced stocks from the US. All stocks are equally weighted. It mean that each stock represents 0.25% of whole index. It does not represent Americas stock market, it just shows the most potent firms.

The most technologically focused is the Nasdaq Composite Index. It was launched in 1971. It consists mostly of hi-tech firms listed on NASDAQ stock market. Many companies listed on NASDAQ do not have headquarters in US.

Lastly, the Russell 2000 is focused on small market capital firms. It was introduced in 1984 as the first small cap benchmark. It is market capitalization-weighted index.

3 Macroeconomic variables

"It is a capital mistake to theorize before one has data. Insensibly one begins to twist facts to suit theories, instead of theories to fit facts." (Doyle, 1985)

What is macroeconomics? In contrast to microeconomics, which focuses solely on individual behavior of a consumer or a specific firm, Macroeconomics is a branch of the economics field studies, how the aggregate economy behaves. To study and correctly access the economy, the macroeconomists use three major macroeconomic indexes, Gross domestic product, unemployment and inflation, which determines the condition of the economy. It was argued by Mankiw (2014) that macroeconomic issues, affect everyone and therefore macroeconomics plays central role in our lives.

3.1 Gross Domestic Product

As the OECD defines it, "the gross domestic product is an aggregate measure of production equal to the sum of the gross values added of all resident institutional units engaged in production (plus any taxes, and minus any subsidies, on products not included in the value of their outputs)" (OECD Statistics, 2001).

Basically the GDP is price tag on country's output. It is calculated as a sum of the investment, private consumption, government spending and net export (exports minus imports). GDP gives important information about the economy. It tells the story, if the economy is expanding or if it is shrinking.[3].

It is also valuable indicator for companies to determine, if the demand for new products is rising or falling. The GDP and also GDP per capita (GDP divided by number of citizens) can be used as measurement of different countries and determine whether it is growing at comparable rate.

[3]The National Bureau of Economic Research (NBER) committee takes about 6-21 month to determine peak and trough of the economy (Nber, 2017)

Although, it is not perfect, GDP can also measure the standards of living. There are several issues with that claim, for example, if country goes through natural disaster and than it rebuilds itself the GDP is growing but one can hardly say that standards of living improved. Also, Gross domestic product does not take into account shadow economy like selling drugs. The idea behind it is that as the products produced by country are more valuable and the country gets richer, people will be better off.

Gross domestic product can be calculated in three different ways. Firstly, there is the expenditure method, which simply adds up all money spend on goods and services. It includes private consumption, government spending, investment and net exports. Secondly, there is production method, which works the other way around. It estimates value of total economic output and than costs of intermediate goods, material and services that are used in process are deducted. Lastly, there us the income approach which adds up income from companies and households in specific year (rents, profits, wages, interest determine GDP). All those methods, if calculated correctly should yield same results. The data on GDP is available on quarterly basis. To get idea of the GDP changes on monthly basis it is useful to use a proxy index.

3.1.1 Industrial Production

The Industrial Production Index (IP) is an economic indicator. It measures real output of manufacturing, mining, electric, and gas utility industries that are located in the United states (FED, 2017). The data is published on monthly basis from Federal reserve and it is seasonally adjusted. The information about production is obtained from private trade associations and government agencies. If the data is not available, it is estimated by using production-worker hours. For the first estimate for specific month 73% of the source data is available.

3.1.2 ISM Manufacturing and Non-Manufacturing Index

The Institute for Supply management (ISM) produces monthly data based on questionnaire given to the companies. The managers are asked about inventory levels, firm's production, employment, etc. Based on those data Indexes are made. The Manufacturing data are available the first day on the next month. No other economic variable of such importance becomes available first thing every month, on a consistent basis. The Non-Manufacturing index data is available in the first week of the next month, which is also amazing. The data are almost not reviewed. The Purchasing Managers index (PMI) for manufacturing is very well known indicator and it is used by professionals on the whole world. In contrast PMI for Non-manufacturing is not as well known and it limitates uses of this index. Based on the data from World Bank about 80% of US economy is created by service sector. Moreover, ISM indexes prove to be excellent forecasters of GDP in real time based on research done by Lahiri and Monokroussos (2013), Banerjee and Marcellino (2006) and Lindsey and Pavur (2005).

3.2 Unemployment

Unemployment rate is a percentage of people in the labor force, who are unemployed and actively looking for a job. Seeking work means contacting potential employers or government agencies like employment office. The official rate includes only those, who are actively looking for job. It does not include people, who are discouraged from looking for a job or people who have settled for part-time work.

Each month the Bureau of Labor Statistics (BLS) announces number of people that are unemployed for previous month. Since not all people in US are eligible for government unemployment benefits and making census of all people would be extremely costly and time consuming the sample method is used. The BLS conducts survey on approximately 110 000 people to determine the unemployment. The chances are 90 percent that the number published represents whole population within ±300 000 people range given that unemployment rate ranges from 7 to 15 million people (BLS, 2017).

3.3 Inflation

Inflation is the rate at which prices of goods and services increase over year. If the prices decrease, then there is a deflation present in the economy. The inflation is interconnected to monetary basis of the currency used in the economy. If the Federal reserve bank decides to print huge amounts of money out of thin air, which are not backed up by real assets than the currency depreciates, in other words we have inflation. The central banks around the globe set inflation target to about 2% - 3% per year, which should be good for economy Fed (2015). Moderate inflation motivates people to invest their money to protect themselves from falling purchasing power of their savings. High investments should encourage steady economic growth. If the inflation is too high it leads to hyperinflation, which can destroy whole economy like in Zimbabwe's case (Hanke, and Kwok, 2009).

There are several ways to measure inflation. The most used is GDP deflator and Consumer price index. The GDP deflator is calculated as Nominal GDP divided by real GDP. It is based on Paasche index. The prices do not change, they are taken from the base year, only quantities change. The GDP deflator takes into account only changes of prices of domestically produced goods, while people buy lot of foreign goods. The GDP deflator as the Paasche index understates the inflation in the economy. Data are provided by US government on quarterly basis. On the other hand, there is Consumer price index (CPI) with fixed basked of goods and the prices are changing. CPI is based on Laspeyres index. Laspeyres index overestimates the inflation because it does not take into account close subsidies of certain products. If the bread becomes more expensive then people would buy more rolls and so the inflation does not have such severe effect on them. In other words, it is not very responsive to changes in consumer preferences. The data are available on monthly basis.

To conclude, both indexes have their ups and downs. Because GDP deflator is published only quarterly, I will use CPI in my further analysis.

4 Methodology

"At first glance, VARs appear to be straightforward multivariate generalizations of univariate autoregressive models. At second sight, they turn out to be one of the key empirical tools in modern macroeconomics."
(Negro, and Schorfheide, 2011)

Vector autoregressive models have become one of the key empirical tool in modern macroeconomics. They date back to 1980, when American economist, Christopher A. Sims, criticized large scale macroeconomic models, the structural models that have been widely used in 1960s and 1970s in applied macroeconomics. Structural models were pioneered by Cowles commission. The basic idea of those models is that variables can be divided into two subgroups, exogenous and endogenous variables. The exogenous variables are defined outside the system and they could be treated independently. Then to solve those equations, strong exclusion restrictions for identifying equations are applied. Those restrictions, have to be backed with a prior theory or statistical justification.

Sims dissatisfaction with those very strong and unrealistic restrictions became known as Sims Critique (Sims, 1980). Sims claimed that so many restrictions are not necessary and all variables in structural models could be argued to be endogenous. Sims proposed the solution, the Vector autoregresive models (VARs). The VARs are fundamentally simple multivariate time-series models designed to capture the joined dynamics of multiple time-series. Each endogenous variable in the system is treated as function of lagged values of all endogenous variables and exogenous variables. The Vector autoregressive models are much simpler and easier to interpret than structural models, where results are "hidden" by complicated structure and many unnecessary assumptions and restrictions (Bjornland, 2000). Sims pointed out that VARs provide more systematic approach to applying restrictions and could help us to better understand relationships between variables. To sum it up, the VARs are based on modeling of time series data without having too much of a prior theory.

4.1 Reduced form of VARs

The reduced form of VAR can be estimated trough ordinary least square method equation by equation. It is consistent and under assumption of normality also efficient (Canova, 1995). The p-order autoregressive process for n endogenous variables is defined as [4]:

$$\boldsymbol{y_t} = \boldsymbol{G}_0 + \boldsymbol{G_1} * \boldsymbol{y_{t-1}} + \boldsymbol{G_2} * \boldsymbol{y_{t-2}} + ... + \boldsymbol{G_p} * \boldsymbol{y_{t-p}} + \boldsymbol{e_t} \quad (1)$$

Where $\boldsymbol{y_t}$ is an one dimensional vector with n number of variables at time t: $\boldsymbol{y_t} = [y_1t, y_2t...y_nt]'$, the $\boldsymbol{G_0}$ is n times one vector of constants (vector of intercepts), $\boldsymbol{G_i}$ is n times n matrix of all coefficients and $\boldsymbol{e_t}$ is n times one vector of white noise innovations. White noise innovations means that they are not serially correlated and the $E[\boldsymbol{e_t}] = 0$. Essentially, the VAR model of n endogenous variables consists of n equations where each endogenous variables is represented as function of its past realizations, meaning that lags to order p of all endogenous variables are included and error term $\boldsymbol{e_t}$.

4.2 Specification and Appropriate number of lags

Specification of a VAR model consists of selecting appropriate variables for a model. Since it is impossible to choose all variables, suitable variables (endogenous) are chosen according to an economic theory, experience or empirical evidence. Next, also exogenous variables can be included into model. It can be time trend, seasonal dummies and other exogenous variables that might have impact on our analysis.

Finally, the model should be parsimonious. It means that model should be estimated with the lowest number of parameters suitable for explaining economic situation. Also, number of lags p included in the model is very important. On the one hand, if the p is short the model may be poorly specified, which implies that residuals are not white noises. On the other

[4] Bold style represents the matrix notation.

hand, if p is longer than it is necessary, too many degrees of freedom will be lost which leads to over fitting. It is because the VAR models are heavenly parametrized. To demonstrate this issue, let there be VAR model consisting of n endogenous variables with p lags than the total number of parameters that have to be estimated is $n^2 * p + n$ under assumption that we also include intercept and no other exogenous variables. This means that degrees of freedom are lost at quadratic rate. If we try to estimate too many coefficients with little data, then the coefficients themselves are poorly specified.

In practice, it is possible to use multidimensional versions of the lag length tests. For example, Akaike information criterion (AIC), Schwartz information criterion (SC), Hanna-Quinn information criterion (HQC) and others. Those criteria are based on trade offs between parsimony and reduction in explained sum of the squares. The Akaike's final prediction error proposed by Hsiao (1981), gives relatively more importance to unbiasedness over efficiency, but is asymptotically inefficient in that, on average, it selects lags that are too long in large samples. In contrast, Schwartz information criterion and Hanna-Quinn information criterion are more efficient, but usually select lags that are too short for the sample. Based on findings Liew (2004), the performance of all test increases substantially as sample size grows and with relatively large sample (120+), HQC is found to outperform the rest in correctly identifying the true lag length, but the problem of over estimation is negligible in all cases (HQC,AIC SC). Ivanov and Kilian (2001) claimed that for monthly VAR models, the Akaike Information Criterion tends to produce the most accurate results.

Based on those findings, the Akaike Information Criterion will be used.

4.3 Stationarity

The stationarity, more precisely covariance-stationarity, is probably the most important specification issue. If time series data are not stationary, then estimation by OLS is biased. Formally, a VAR is covariance-stationary, if the expected value of $\boldsymbol{y_t}$ does not depend on the time and the covariance matrix of $\boldsymbol{y_t}$ and $\boldsymbol{y_{t+j}}$ does not depend on time t, but only on time difference between two periods, the j. To summarize, the VAR is covariance-stationary, if it has finite and time-invariant first and second moment.

The condition for a VAR process to be covariance-stationary is that all np roots of the characteristic polynomial: $det(\boldsymbol{I_n} - \boldsymbol{G_1} * \boldsymbol{L^1} - \boldsymbol{G_2} * \boldsymbol{L^2} - ... - \boldsymbol{G_p} * \boldsymbol{L^P}) = 0$ are outside the unit imaginary circle. Its characteristic polynomial can be derived from equation (1), where $\boldsymbol{L^i}$ stands for lag operator and $\boldsymbol{I_n}$ is identity matrix.

In practice, statistical packages like EViews or Gretl calculate inverse roots of the characteristic polynomial, meaning that those roots should lie within the unit imaginary circle.

When some of the variables are not stationary, they are often transformed. Usually log differences, log levels or growth rates are applied.

4.3.1 Testing data for Stationarity

In general, it is useful to test data for stationarity prior to building the economic model. For those purposes Kwiatkowski Phillips Schmidt Shin (KPSS) test or the Augmented Dickey-Fuller test are applied. KPSS is used for testing a null hypothesis that a variable is stationary or trend-stationary against the alternative of a unit root (Kwiatkowski, Phillips, Schmidt, and Shin, 1992). In contrast, other test for stationarity, like Augmented Dickey-Fuller test have the null hypothesis that variable follows unit root process against stationarity.

4.4 Tests for Residual Autocorrelation and Heteroskedasticity

Serial correlation and Heteroskedasticity are not such a big issues as non-stationary data. The beta coefficients are calculated correctly, but the test statistics like t-test and F-test are not right. Also, the Grangar casualty test, which I will talk more about in next subsection is not valid. That is why it is important to test for autocorelation and heteroskedasticity and apply robust statistics, if they are present in model.

In simple terms, serial correlation means that the errors in two different time periods are correlated. Testing for serial correlation in VAR models can be done by either Portmanteau and Breusch-Godfrey-LM tests. The Portmanteau test's null hypothesis H_0 is that all residual autocovariances are zero. The H_1 is that at least one autocovariance is non zero, meaning that serial correlation is present. The Portmanteu test is very good for testing of high order serial correlation, but for smaller order the Breusch-Godfrey-LM test is more suitable (Lutkepohl, 2001). The Breusch-Godfrey-LM test is much simpler and uses past error terms to find out if there is correlation of not. This test evaluates coefficients of this equation $u_t = \beta_1 * u_{t-1} + ... + \beta_h * u_{t-h} + e_t$ with null hypothesis that all betas are equal to zero. The alternative hypothesis is that at least one beta is not zero and so the serial correlation is present.

Heteroskedasticity means that the variance of u_t is not same for all t. Testing for heteroskedasticity can be done by White test or by Autoregressive conditional heteroskedasticity test. The White test is based on calculating of F-statistics of the model $u_t^2 = \beta_0 + \beta_1 * Y_i + \beta_1 * Y_i^2$, where u_t represents squared residuals from original regression model and Y represents predicted dependent variable from original model. The Autoregressive conditional heteroskedasticity test is more complicated, but the null hypothesis and the alternative hypothesis are the same as in the White test.

In case, when heteroskedasticity and serial correlation are present in the model the statistical package in Gretl offers robust estimator of standard errors called HAC (Heteroskedasticity autocorrelated consistent). In essence, it specifies how far away in the time the serial correlation is present. Then the autocorrelated errors over the chosen time window are "averaged". The statistical software decides for the appropriate number of errors to average (this parameter is called bandwidth) and there are two methods of averaging called kernel (Bartlett kernel or Parzen kernel). According to Kiefer and Vogelsang (2000), the Bartlett kernel delivers the greatest power within a group of popular kernels.

4.5 Granger Causality Analysis

Sir Clive William John Granger in 1969 devised statistical method for casual testing between different variables. It has became known as Granger-causality. Granger suggests that past can predict future but not vice versa.

According to Granger, variable "x" causes different variable "y", if past values of "x" can predict "y' better than past values of "y". So, if past "x's" help to explain variation in present "y" than "x" Granger causes "y". More formally, if we assume one equation out of simple case of VAR model with two endogenous variables of the p order of 2 with intercept,

$$y_{1,t} = \beta_0 + \beta_1 * y_{1,t-1} + \beta_2 * y_{1,t-2} + \beta_3 * y_{2,t-1} + \beta_4 * y_{2,t-2} + e_t \quad (2)$$

Than the $y_{t,2}$ does not Granger cause the $y_{t,1}$, if and only if $\beta_3 = \beta_4 = 0$. Granger casualty can then be calculated by simple F-test. Calculating Granger causality for more than two variables is more complicated. In practice, it is often calculated for bi-variate process.

The results, from empirical research, should be interpreted as suggestive rather than absolute. The Granger causality depends on the specification of the model. It may be the case that if we add to a model new variable that drives both variables of the bi-variate process, the casual structure may in matter of fact disappear. It is because of the violation of the ceteris paribus condition. Meaning that our explanatory variable may have effect on other variable that has effect on explained variable.

5 Data

To uncover causal relationships between the Stock market and macroeconomic variables the time series data from the United states on monthly basis from June 1950 to October 2016.

Fist of all, the reason for using data from United States of America is because it is the biggest and most influential economy in the world. The public announcements of the prospects of the US have even significant effect on other foreign stock markets around the globe (Nikkinen, Omran, Sahlstrom, and Aijo, 2016). For future studies it is possible to broaden my work and look if the same results could be achieved in other parts of the world.

Secondly, the data will be on the monthly basis. The main reason behind this decision is the nature of the Stock market. The stock market reacts almost instantly to any new information available. According to the "efficient market" theory proposed by Fama (1965), who claimed that in an efficient market, on the average, competition will cause the full effects of new information on intrinsic values to be reflected "instantaneously" in actual prices. Because of that, too much information would be lost, if quarterly or annual data were used instead. Also, with almost 800 observations, it is much easier to argue that statistical theory like central limit theorem work properly.

Lastly, the period from January 1950 to October 2016 is longest data set that could have been found free of charge from the online sources.

5.1 Transformation of the data

In my analysis, the S&P500 index, Will 5000 index and oil prices will be used. All of these are available on daily basis. Based on empirical research that have been done before me (Choia, Hauserb, and Kopeckya, 1999)), I will use monthly averages of those data. If opens or closes on ether beginning or the end of the month were used, the high fluctuation of the stock market could overestimate the month to month changes.

In addition, macroeconomic data will be used namely inflation, unemployment and proxies for the GDP. Those data will be used as they are published from Federal government of the US. Lastly, simple quarterly seasonal dummies and time trends will be also used in the analysis.

5.2 Testing for Stationarity

To avoid potential spurious relationship in my further VAR models, the tests for stationarity will be performed on all variables of interest.

Firstly, the null hypothesis of the Augmented Dickey–Fuller Test could not be rejected in the case of unemployment, proxies for GDP, namely IP, ISM manufacturing and non-manufacturing index, S&P500, Willshire 5000 index, oil on the 99% confidence interval. To check the robustness of the results I performed KPSS test and I was able to reject null hypothesis of stationary data at 99% confidence interval. In the case of the inflation, I was able to reject null hypothesis of unit root process of Augmented Dickey–Fuller Test on 95% confidence interval. To check robustness of this result I performed KPSS test, which rejected the null hypothesis of stationarity at 99% confidence interval. This implies that inflation does not exactly follow the unit root process, but also it is not stationary.

To treat the problem of non-stationary data , the transformation of inflation, unemployment, industrial production, ISM manufacturing index and ISM non-manufacturing index into differences was made. In case of the S&P500 log differences are applied, based on the fact that since the begging of my data set (January 1950) has the S&P500 gone from 16 to almost 2200 as it is today. To correctly measure the same percent changes the logarithmic form will be applied. The differences are used so the unit root process is eliminated. The exact same procedure was used on Will 5000 with exactly same results. In case of the oil I transformed it in differences and log differences to find out which transformation better fits the model.

To confirm my assumptions the Kwiatkowski Phillips Schmidt Shin test was done on the all transformations and I was not able to reject null hypothesis of stationarity, trend staionarity at 90 percent confidence interval.

From now on, if the variable of the interest is mentioned the appropriate stationary transformation is meant.

6 Analysis

In this section, the hypothesis about the relationship between the stock market and macroeconomic variables will be tested. The same procedures will be performed as described in methodology section using Gretl and R.

The Table I, bellow ,explains all variables used in Vector autoregression analysis in the whole Analysis section. Basic notation behind those signs is that "diff_variable" means variable in time t minus variable in time t-1. The "log_variable" represents natural logarithm taken from variable.

Table I	
Δunemployment	Difference in the unemployment
Δlog_SP500	Logarithmic difference in S&P500 index
Δlog_will5000	Logarithmic difference in Willshire 5000 index
Δinflation	Difference in the inflation
Δindp	Difference in the Industrial production
Δmanifacturing	Difference in the ISM manufacturing data
Δnonmanifacturing	Difference in the ISM non manufacturing
Δoil	Difference in the oil price
d	Dummy variable: 1=US economy in expansion, 0= US economy is in contraction
q_i	Dummy variable for quartal

6.1 Can the Stock market predict Gross Domestic Product?

Hypothesis 1: The volatility of the Stock market has build inside information about future Gross domestic product.

The first hypothesis is based mostly on the work done by Beetsma and Giuliodori (2011) and Choudhry, Papadimitriou and Shabi (2016). To test this hypothesis, the VAR model will be used to explain relationships between the stock market and proxies for the GDP. In the main model the industrial production index will be used to confirm or reject the Hypothesis 1. Later, also other proxies will be used based on the fact that nowadays the industrial production share on the total GDP is only about 20% (Worldbank, 2017).

6.1.1 The main model GDP

The main model consists of two endogenous variable, the IP, S&P500, and some exogenous variables, a constant, oil prices and quarterly dummies from June 1950 to October 2016. The decision for the oil prices being exogenous is based on the paper from Sadorsky (1999) whose results suggest that changes in oil prices impact economic activity, but changes in economic activity have little impact on oil prices. Furthermore, Huang, Masulis and Stoll (1996) concluded that prices of oil futures have little correlation with stocks, besides the stocks of oil companies. The main focus of this thesis is on the predicting power of the stock market, but in further studies it is possible to focus on prices of commodities like oil or gold. (the difference in log oil prices were not statistically significant, therefore difference in oil prices are used).

To decide for appropriate number of lags, the lag criterion tests are also calculated. The AIC resulted in six, HQC three and SC also three, therefore six will be used. To test for stationarity of the model, the inverse roots were printed and all of them were safely inside the unit root circle.

Furthermore, the Breusch-Godfrey LM test for serial correlation rejected null hypothesis at 95% confidence interval. Both, White tests for heteroskedasticity and ARCH test, resulted in to rejection of the null hypothesis of homoskedasticity at 99% confidence interval. To treat issues, with serial correlation and heteroskedasticity, the robust errors will be used.[5]

The results of the heteroskedasticity and auto correlation robust summary of the the main model can be seen in the Table 1 bellow. In the first equation, where the industrial production is explained by its lags and lagged values of S&P500, the Vector autoregressive model achieved to predict about quarter of variations in industrial production, which is decent result. The coefficients of S&P500 prices are all positive, which is in line with intuition and the second, third, fourth and sixth are all statistically significant at 90% confidence interval. Based on the Granger causality F-test, on the one hand, the S&P500 Granger causes the change in industrial production with zero p-value, on the other hand, I failed to reject null hypothesis that all lagged

[5] The Bartlett kernel will be used trough the analysis

values of the industrial production Granger cause the transformed S&P500, in matter of fact none of the lags is statistically important on 90% confidence interval.

TABLE 1, lag order 6

Equation 1: Δindp

	Coefficient	Std. Error	t-ratio	p-value
const	−0.0183	0.0290	−0.6317	0.5278
$\Delta\text{indp}_{(t-1)}$	0.0969	0.0522	1.8536	0.0642
$\Delta\text{indp}_{(t-2)}$	0.1126	0.0346	3.2517	0.0012
$\Delta\text{indp}_{(t-3)}$	0.1466	0.0453	3.2327	0.0013
$\Delta\text{indp}_{(t-4)}$	0.0842	0.0510	1.6512	0.0991
$\Delta\text{indp}_{(t-5)}$	−0.0234	0.0333	−0.7042	0.4815
$\Delta\text{indp}_{(t-6)}$	0.0564	0.0293	1.9230	0.0548
$\Delta\text{log\_SP500}_{(t-1)}$	0.5541	0.4330	1.2797	0.2010
$\Delta\text{log\_SP500}_{(t-2)}$	2.3366	0.7127	3.2783	0.0011
$\Delta\text{log\_SP500}_{(t-3)}$	2.0805	0.4796	4.3374	0.0000
$\Delta\text{log\_SP500}_{(t-4)}$	0.5821	0.4574	1.2726	0.2036
$\Delta\text{log\_SP500}_{(t-5)}$	0.2703	0.4692	0.5763	0.5646
$\Delta\text{log\_SP500}_{(t-6)}$	0.9173	0.4163	2.2033	0.0279
q_2	0.0127	0.0290	0.4389	0.6609
q_3	0.0270	0.0425	0.6365	0.5246
q_4	0.0993	0.0431	2.3005	0.0217
Δoil	0.0062	0.0070	0.8758	0.3814

Mean dependent var	0.1105	S.D. dependent var	0.4623
Sum squared resid	128.3070	S.E. of regression	0.4058
R^2	0.2449	Adjusted R^2	0.2294
$F(16, 779)$	14.1194	P-value(F)	7.54e–34

Granager causality F-tests of zero restriction

Null hypothesis:	F-Statistics:	p-value:
All lags of Δlog_SP500 do not Granger cause Δindp.	12.5681	[0.0000]

Equation 2: Δlog_SP500

	Coefficient	Std. Error	t-ratio	p-value
const	0.0066	0.0026	2.5157	0.0121
$\Delta \text{indp}_{(t-1)}$	0.0037	0.0054	0.6915	0.4895
$\Delta \text{indp}_{(t-2)}$	0.0030	0.0036	0.8512	0.3949
$\Delta \text{indp}_{(t-3)}$	−0.0036	0.0030	−1.2143	0.2250
$\Delta \text{indp}_{(t-4)}$	−0.0025	0.0031	−0.8130	0.4165
$\Delta \text{indp}_{(t-5)}$	−0.0010	0.0023	−0.4290	0.6680
$\Delta \text{indp}_{(t-6)}$	0.0018	0.0030	0.6001	0.5486
$\Delta \text{log\_SP500}_{(t-1)}$	0.2402	0.0368	6.5252	0.0000
$\Delta \text{log\_SP500}_{(t-2)}$	−0.0712	0.0366	−1.9461	0.0520
$\Delta \text{log\_SP500}_{(t-3)}$	0.0446	0.0375	1.1872	0.2355
$\Delta \text{log\_SP500}_{(t-4)}$	0.0142	0.0361	0.3932	0.6943
$\Delta \text{log\_SP500}_{(t-5)}$	0.1133	0.0446	2.5397	0.0113
$\Delta \text{log\_SP500}_{(t-6)}$	−0.1050	0.0441	−2.3772	0.0177
q_2	−0.0037	0.0034	−1.0846	0.2784
q_3	−0.0059	0.0034	−1.7205	0.0857
q_4	0.0005	0.0033	0.1595	0.8733
Δoil	0.0014	0.0006	2.0425	0.0414

Mean dependent var	0.0059	S.D. dependent var	0.0349
Sum squared resid	0.8643	S.E. of regression	0.0333
R^2	0.1087	Adjusted R^2	0.0903
$F(16, 779)$	6.1319	P-value(F)	6.34e–13

Granger causality F-tests of zero restriction

Null hypothesis:	F-Statistics:	p-value:
All lags of Δindp do not Granger cause Δlog_SP500.	0.4681	[0.8322]

6.1.2 Robustness of the S&P500

In order, to test the robustness of the results from the main model the S&P500 index is replaced by Will 5000 index. Since Will 5000 is only available since 1971, the model based on S&P500 is also re-estimated on the same time period.

In case of the S&P500 model reduced to time period of 1970-2016 the lag specification tests, stationary test and heteroskedasticity test gave same results as those in the main model. The Breusch-Godfrey LM test failed to reject null hypothesis of no serial correlation at 90% confidence interval. The heteroskedasticity robust t-tests and F-test were therefore applied. For the results, please see appendix the Table 2.

In the case of the Will 5000 index, the model is defined exactly as the main model, but the S&P500 is replaced with the Will 5000 index. The lag specification test have different results, namely the Akaike resulted in four, Hanna-Quinn three and Schwartz also tree. Therefore, only four lags will be used in this case. The tests for serial correlation, stationary test and heteroskedasticity resulted exactly the same as in the case of the main model reduced to 1970-2016 time period. For the results, please see appendix the Table 3.

Based on the results from both VARs it is obvious that results are robust.

6.1.3 ISM manufacturing model

The ISM manufacturing model consists of two endogenous variable, the ISM manufacturing index and S&P500, and some exogenous variables, a constant difference is oil prices and quarterly dummies from the January 1970 to October 2016.

The tests for lag specifications resulted in two appropriate lag. All inverse roots are safely inside the unit circle. I failed to reject null hypothesis of Breusch-Godfrey LM test at 90% confidence interval. Both heteroskedasticity test rejected null hypothesis at 99% confidence interval. Therefore, heteroskedasticity robust t-statistics and F-tests were used.

The results are shown at Table 4. The Grager causality test confirms that S&P500 Granger causes the ISM manufacturing index, but not vice versa. The stock market can to some extent predict the variations of the ISM manufacturing but the results are not as good as in the case of industrial production.

6.1.4 ISM non-manufacturing model

The ISM non-manufacturing model consists of two endogenous variable, the ISM non-manufacturing index, S&P500, and some exogenous variables, a constant, oil prices and quarterly dummies from the August 1997 to October 2016. The tests for lag specifications resulted in two appropriate lag. All inverse roots are safely inside the unit circle. I failed to reject null hypoithesis of Breusch-Godfrey LM test at 90% confidence interval. Both heteroskedasticity test rejected null hypothesis at 99% confidence interval. Therefore, heteroskedasticity robust t-statistics and F-tests were used.

The results can be seen at Table 4. In the first equation, where d the ISM non-manufacturing index is the explained variable, the first lag of S&P500 is statistically significant with p value equal to 1%, both lags of ISM non-manufacturing and differences in oil prices. The R^2 is pretty decent. In the second equation, where the transformation S&P500 is the explained variable only first lag of S&P500 is statistically significant. The Granger causality F-test reject the null hypothesis that S&P500 does not cause the change in ISM non-manufacturing at 99% confidence interval. In the opposite, case I failed to reject null hypothesis at 90% confidence interval.

6.2 Can the Stock market predict unemployment ?

Hypothesis 2: The volatility of the Stock market can indeed predict business cycle, and therefore can also predict unemployment.

Generally speaking, the business cycle is measured and tracked in terms of GDP and unemployment – GDP rises and unemployment shrinks during expansion phases, while reversing in periods of recession. The relationships is also known as Okun's law proposed by Arthur Melvin Okun, in 1962 (Ball, Jalles, and Loungani, 2015). Therefore, if the past realizations of the stock market can predict Gross domestic product they should also be able to predict the unemployment.

To test this Hypotheses the main model will be build with unemployment and stock market and other variables. If the stock market will be able to partly predict unemployment than the dummy variable, where one means that economy is in the expansion and zero means that the economy is in recession will be added. If the past realizations of the stock market cease to be statistically significant, then the Hypothesis 2 will be proved.

6.2.1 The main model Unemployment

The main model consists of three endogenous variables, the unemployment rate, S&P500 and the inflation, and an exogenous variable differences of the oil prices from the June 1950 to October 2016.

To decide, for appropriate number of lags, the Akaike information criterion, Schwartz information criterion and Hanna-Quinn information criterion were calculated. The tests were limited to maximum of the ten lags. This decision was made due to fact that differences in the inflation are heavily serial correlated and this fact highly inflates the number of appropriate lags for whole model. The inflation is not main variable of the interest and was added due to theoretical reasons. (Phillips curve) The Akaike resulted in six, Hanna-Quinn three and Schwartz also tree. Based on the results it would be more appropriate to include six, just to be sure not to loose any important information.

To test for stationarity of the model the inverse roots were printed and all of them are safely inside the unit root circle.

Furthermore, the Breusch-Godfrey LM test for serial correlation rejected null hypothesis at 99% confidence interval. Both, White tests for heteroskedasticity and ARCH test, resulted in to rejection of the null hypothesis of homoskedasticity at 99% confidence interval. To treat issues with serial correlation and heteroskedasticity the robust errors will be used.

The results of the heteroskedasticity and auto correlation robust summary of the the main model can be seen in the Table 6 bellow. Th first equation, where the unemployment is explained variable, the Var model managed to explain about one fifth of all variations which is decent. The first, third, fourth and sixth lags of the S&P500 are statistically significant at 95% confidence interval. Also almost all lags of the unemployment are statistically and first and fourth lag of the inflation. The coefficients of the lagged S&P500 are all negative with is in line with the intuition.

Based on the Granger causality tests, both unemployment and S&P500 Granger cause each other . In other words, it is possible to reject null hypothesis in both cases at 95% confidence interval.

If we add the dummy variable d as an exogenous variable (please see Table 7 for results), then all lags of S&P500 stops to be statistically significant at 90% confidence interval the R^2 is .28 higher than in the previous model. This means that Stock market indeed have some predictive power of the GDP and therefore can predict the unemployment.

The robustness of the S&P500 was tested in the same way as in the previous section in the case of the GDP main model. The S&P500 was proved to be robust.

Table 6, lag order 6

Equation 1: Δunemployment

	Coefficient	Std. Error	t-ratio	p-value
const	0.0153	0.0069	2.2225	0.0265
Δunemployment$_{(t-1)}$	0.0253	0.0415	0.6106	0.5417
Δunemployment$_{(t-2)}$	0.1734	0.0356	4.8668	0.0000
Δunemployment$_{(t-3)}$	0.0911	0.0402	2.2661	0.0237
Δunemployment$_{(t-4)}$	0.1007	0.0358	2.8122	0.0050
Δunemployment$_{(t-5)}$	0.0894	0.0350	2.5523	0.0109
Δunemployment$_{(t-6)}$	0.0486	0.0412	1.1813	0.2379
Δlog_SP500$_{(t-1)}$	-0.4341	0.1988	-2.1834	0.0293
Δlog_SP500$_{(t-2)}$	-0.2947	0.1994	-1.4781	0.1398
Δlog_SP500$_{(t-3)}$	-0.5423	0.2019	-2.6855	0.0074
Δlog_SP500$_{(t-4)}$	-0.5424	0.2152	-2.5199	0.0119
Δlog_SP500$_{(t-5)}$	-0.3026	0.1856	-1.6300	0.1035
Δlog_SP500$_{(t-6)}$	-0.4219	0.1740	-2.4247	0.0155
Δinflation_(t-1	0.0092	0.0272	0.3404	0.7336
Δinflation$_{(t-2)}$	0.0375	0.0183	2.0443	0.0413
Δinflation$_{(t-3)}$	-0.0203	0.0228	-0.8885	0.3746
Δinflation$_{(t-4)}$	-0.0090	0.0229	-0.3945	0.6933
Δinflation$_{(t-5)}$	0.0462	0.0226	2.0444	0.0413
Δinflation$_{(t-6)}$	-0.0212	0.0214	-0.9912	0.3219
Δoil	-0.0007	0.0018	-0.4196	0.6749

Mean dependent var	-0.0006	S.D. dependent var	0.1957
Sum squared resid	24.3294	S.E. of regression	0.1770
R^2	0.2009	Adjusted R^2	0.1814
$F(16, 776)$	9.4804	P-value(F)	4.78e–25

Granger causality F-tests of zero restriction

Null hypothesis:	F-Statistics:	p-value:
All lags of Δlog_SP500 do not Granger cause Δunemployment.	6.6109	[0.0000]

6.2.2 Small model - unemployment

In this section, the main model of the unemployment will be reduced to the period of the last 20 years,(October 1996 - october 2016) to see how the unemployment and the stock market interact in the age of the Internet.[6]

The Small model - unemployment consists of the exactly same variables as the Main model, except the inflation is not included because it was not statistically significant (See Table 8).

The tests for lag specification resulted with six optimum lags. Bresch-Godfrey Lm test could not reject null hypothesis at 90% confidence interval, in the case of the test for heteroskedasticity the ARCH-test resulted in p value of 0.1003 and White test in the p value of 0.0619. Based on these information it would be safer to use the heteroskedasticity robust standard errors.

To test for stationarity of the model the inverse roots were printed and all of them are safely inside the unit root circle.

The results can be seen in the Table 9. In the first equation, where unemployment is explained variable The first, second and fourth lags of S&P500 are statistically significant, which is good sign. In the case of unemployment the second, fifth and sixth lags are statistically significant. The R^2 is almost 0.3 which is better than in the case of the main model. The Granger causality test can be rejected at 99% confidence interval, meaning that it is highly probable that lags of S&P500 cause the unemployment, on the one hand, and it is not possible to reject null hypothesis of Grange causality test at 90% confidence interval that unemployment causes S&P500.

[6]It was argued that the spread of the internet begin somewhat between 1993-1996 Cooper (2016)

6.3 Final model

In previous chapters of the analysis, I have proved that the stock market has effect on the proxies of the GDP and because of that it can also predict unemployment (GDP and unemployment are interconnected trough Okun's law). In the final model, the S&P500, industrial production, unemployment and inflation are included as endogenous variables to see if the stock market (S&P500) can predict unemployment, if also past realizations of the industrial production are present in the model. The exogenous variables are oil prices and seasonal dummies (dummy for second quarter was excluded, because it is not statistically significant). The whole period is included.

The test for appropriate lags resulted in six. The maximum number of lags was set to 10 because the inflation is heavily serially correlated.

To test for stationarity of the model the inverse roots were printed and all of them are safely inside the unit root circle.

Furthermore, the Breusch-Godfrey LM test for serial correlation rejected null hypothesis at 99% confidence interval. Both, White tests for heteroskedasticity and ARCH test, resulted in to rejection of the null hypothesis of homoskedasticity at 99% confidence interval. To treat issues with serial correlation and heteroskedasticity the robust errors will be used.

The results of the heteroskedasticity and auto correlation robust summary of the the final model can be seen in the Table 10 in Appendix A. The S&P500 remains still significant, in the case of the first equation, where the unemployment is explained and also in the second equation where the IP explained, but we can see that only lags of S&P500 are statistically significant at 90% confidence interval compared to five in case of main model of the unemployment in previous section. The final model managed to predict about one quarter in the first and the second equation. In case of the first and second equation the Granger causality test rejected null hypotheses that all lags of the S&P500 are not significant. In contrast, in the third equation, where the stock market is explained, I failed to reject null hypothesis of Granger causality test in case of industrial production.

Conclusion

In this thesis, I have explored the causal relationships between the stock market and macroeconomic variables, namely the Industrial production index, the ISM index for manufacturing, the ISM index for non-manufacturing and unemployment with the focus on predicting capabilities of the past realizations of the stock market index, S&P500 on GDP proxies and unemployment over the period going from the mid 1950 until late 2016. All data are from the United states of America.

In the first section of the analysis, the first hypothesis concerning, if the stock market can predict GDP, was tested using VAR model. The main model, where the stock market and Industrial production were the endogenous variables, concludes that the stock market can predict the Industrial production and is able to explain about one quarter of all variations in Industrial production over the whole time period. The Granger causality test rejected null hypothesis, that the stock market does not Granger cause the Industrial production with p value smaller than 0.0001, but I was not able to reject null hypothesis at 90% confidence interval that Industrial production does not Granger causes the stock market. The robustness of the results involved the replacement of the S&P500 index with the Wilshire 5000 index with almost identical results. In case of ISM manufacturing index, the stock market could predict the index but the explained variation was relatively small compared to main model. Lastly, the stock market managed to predict almost one fifth of the ISM non-manufacturing index, the index of the services, over last 20 years.

In the second section of the analysis, the second hypothesis concerning, if the stock market can predict unemployment, was tested using VAR model. The main model, where the stock market, unemployment and inflation where the endogenous variables concludes that the stock market can predict unemployment and is able to explain about one fifth of all variations in unemployment over the whole time period. The Granger causality test rejected null hypothesis that the stock market does not cause the unemployment and also vice versa at 95% confidence interval. In the case of the small model, where I focused only on the last 20 years the inflation ceased to be statistically significant, and therefore only unemployment and the stock market were included as endogenous variables. The small model achieved prediction on scale equal to almost one third of variations of the unemployment. In contrast to main model, Granger causality test failed to reject null hypothesis that the unemployment Granger causes the stock market at 90% confidence interval.

In the third section of the analysis, I had included the S&P500, IP, inflation and unemployment as endogenous variables in to VAR model and proved that even if the IP is included inside the model to predict the unemployment, the past realizations of the stock market are still statistically significant, and therefore the stock market can predict the unemployment beyond predicting only future IP which is interconnected with the unemployment through Okun's law.

In conclusion, I would like to say that the analysis was successful and the results of VAR were in favor of both hypotheses. To extend my work, it is possible to check, if the relationship holds also in other countries around the world. It is also possible to add more variables to see, if even better results in predicting the GDP and unemployment could be achieved.

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List of tables

Appendix A

TABLE 1, lag order 6

Equation 1: Δindp

	Coefficient	Std. Error	t-ratio	p-value
const	−0.0183	0.0290	−0.6317	0.5278
$\Delta\text{indp}_{(t-1)}$	0.0969	0.0522	1.8536	0.0642
$\Delta\text{indp}_{(t-2)}$	0.1126	0.0346	3.2517	0.0012
$\Delta\text{indp}_{(t-3)}$	0.1466	0.0453	3.2327	0.0013
$\Delta\text{indp}_{(t-4)}$	0.0842	0.0510	1.6512	0.0991
$\Delta\text{indp}_{(t-5)}$	−0.0234	0.0333	−0.7042	0.4815
$\Delta\text{indp}_{(t-6)}$	0.0564	0.0293	1.9230	0.0548
$\Delta\text{log\_SP500}_{(t-1)}$	0.5541	0.4330	1.2797	0.2010
$\Delta\text{log\_SP500}_{(t-2)}$	2.3366	0.7127	3.2783	0.0011
$\Delta\text{log\_SP500}_{(t-3)}$	2.0805	0.4796	4.3374	0.0000
$\Delta\text{log\_SP500}_{(t-4)}$	0.5821	0.4574	1.2726	0.2036
$\Delta\text{log\_SP500}_{(t-5)}$	0.2703	0.4692	0.5763	0.5646
$\Delta\text{log\_SP500}_{(t-6)}$	0.9173	0.4163	2.2033	0.0279
q_2	0.0127	0.0290	0.4389	0.6609
q_3	0.0270	0.0425	0.6365	0.5246
q_4	0.0993	0.0431	2.3005	0.0217
Δoil	0.0062	0.0070	0.8758	0.3814

Mean dependent var	0.1105	S.D. dependent var	0.4623
Sum squared resid	128.3070	S.E. of regression	0.4058
R^2	0.2449	Adjusted R^2	0.2294
$F(16, 779)$	14.1194	P-value(F)	7.54e–34

Granger causality F-tests of zero restriction

Null hypothesis:	F-Statistics:	p-value:
All lags of Δlog_SP500 do not Granger cause Δindp.	12.5681	[0.0000]

TABLE 1, lag order 6

Equation 2: Δlog_SP500

	Coefficient	Std. Error	t-ratio	p-value
const	0.0066	0.0026	2.5157	0.0121
$\Delta \text{indp}_{(t-1)}$	0.0037	0.0054	0.6915	0.4895
$\Delta \text{indp}_{(t-2)}$	0.0030	0.0036	0.8512	0.3949
$\Delta \text{indp}_{(t-3)}$	−0.0036	0.0030	−1.2143	0.2250
$\Delta \text{indp}_{(t-4)}$	−0.0025	0.0031	−0.8130	0.4165
$\Delta \text{indp}_{(t-5)}$	−0.0010	0.0023	−0.4290	0.6680
$\Delta \text{indp}_{(t-6)}$	0.0018	0.0030	0.6001	0.5486
$\Delta \text{log\_SP500}_{(t-1)}$	0.2402	0.0368	6.5252	0.0000
$\Delta \text{log\_SP500}_{(t-2)}$	−0.0712	0.0366	−1.9461	0.0520
$\Delta \text{log\_SP500}_{(t-3)}$	0.0446	0.0375	1.1872	0.2355
$\Delta \text{log\_SP500}_{(t-4)}$	0.0142	0.0361	0.3932	0.6943
$\Delta \text{log\_SP500}_{(t-5)}$	0.1133	0.0446	2.5397	0.0113
$\Delta \text{log\_SP500}_{(t-6)}$	−0.1050	0.0441	−2.3772	0.0177
q_2	−0.0037	0.0034	−1.0846	0.2784
q_3	−0.0059	0.0034	−1.7205	0.0857
q_4	0.0005	0.0033	0.1595	0.8733
Δoil	0.0014	0.0006	2.0425	0.0414

Mean dependent var	0.0059	S.D. dependent var	0.0349
Sum squared resid	0.8643	S.E. of regression	0.0333
R^2	0.1087	Adjusted R^2	0.0903
$F(16, 779)$	6.1319	P-value(F)	6.34e–13

Granager causality F-tests of zero restriction

Null hypothesis:	F-Statistics:	p-value:
All lags of Δindp do not Granger cause Δlog_SP500.	0.4681	[0.8322]

Table 2, lag order 6

Equation 1: Δindp

	Coefficient	Std. Error	t-ratio	p-value
const	−0.0265	0.0423	−0.6279	0.5303
$\Delta\text{indp}_{(t-1)}$	0.0554	0.0845	0.6558	0.5122
$\Delta\text{indp}_{(t-2)}$	0.1274	0.0496	2.5652	0.0106
$\Delta\text{indp}_{(t-3)}$	0.1720	0.0559	3.0727	0.0022
$\Delta\text{indp}_{(t-4)}$	0.0958	0.0430	2.2250	0.0265
$\Delta\text{indp}_{(t-5)}$	−0.0182	0.0372	−0.4895	0.6247
$\Delta\text{indp}_{(t-6)}$	0.0623	0.0360	1.7311	0.0840
$\Delta\text{log\_SP500}_{(t-1)}$	0.5120	0.5519	0.9278	0.3539
$\Delta\text{log\_SP500}_{(t-2)}$	2.6116	0.7263	3.5955	0.0004
$\Delta\text{log\_SP500}_{(t-3)}$	2.7530	0.6020	4.5726	0.0000
$\Delta\text{log\_SP500}_{(t-4)}$	0.6145	0.6433	0.9552	0.3399
$\Delta\text{log\_SP500}_{(t-5)}$	−0.2221	0.6382	−0.3483	0.7278
$\Delta\text{log\_SP500}_{(t-6)}$	1.0060	0.5584	1.8016	0.0722
q_2	0.0194	0.0502	0.3868	0.6991
q_3	0.0239	0.0595	0.4028	0.6873
q_4	0.1308	0.0549	2.3826	0.0175
Δoil	0.0065	0.0106	0.6108	0.5416

Mean dependent var	0.1195	S.D. dependent var	0.5188
Sum squared resid	106.9999	S.E. of regression	0.4480
R^2	0.2758	Adjusted R^2	0.2541
$F(16, 533)$	11.7905	P-value(F)	1.61e–26

Granger causality F-tests of zero restriction

Null hypothesis:	F-Statistics:	p-value:
All lags of Δlog_SP500 do not Granger cause Δindp	8.8153	[0.0000]

Table 2, lag order 6

Equation 2: Δlog_SP500

	Coefficient	Std. Error	t-ratio	p-value
const	0.0073	0.0031	2.2925	0.0223
$\Delta\text{indp}_{(t-1)}$	0.0052	0.0059	0.8712	0.3840
$\Delta\text{indp}_{(t-2)}$	0.0056	0.0032	1.7501	0.0807
$\Delta\text{indp}_{(t-3)}$	−0.0031	0.0032	−0.9742	0.3304
$\Delta\text{indp}_{(t-4)}$	−0.0044	0.0033	−1.3532	0.1766
$\Delta\text{indp}_{(t-5)}$	−0.0012	0.0031	−0.4113	0.6810
$\Delta\text{indp}_{(t-6)}$	0.0014	0.0030	0.4813	0.6305
$\Delta\text{log\_SP500}_{(t-1)}$	0.2505	0.0474	5.2807	0.0000
$\Delta\text{log\_SP500}_{(t-2)}$	−0.0838	0.0491	−1.7081	0.0882
$\Delta\text{log\_SP500}_{(t-3)}$	0.0459	0.0479	0.9570	0.3390
$\Delta\text{log\_SP500}_{(t-4)}$	−0.0172	0.0493	−0.3501	0.7264
$\Delta\text{log\_SP500}_{(t-5)}$	0.1019	0.0507	2.0094	0.0450
$\Delta\text{log\_SP500}_{(t-6)}$	−0.1066	0.0515	−2.0693	0.0390
q_2	−0.0026	0.0038	−0.6855	0.4933
q_3	−0.0088	0.0043	−2.0256	0.0433
q_4	−0.0013	0.0042	−0.3185	0.7502
Δoil	0.0013	0.0006	1.9512	0.0516

Mean dependent var	0.0057	S.D. dependent var	0.0365
Sum squared resid	0.6384	S.E. of regression	0.0346
R^2	0.1307	Adjusted R^2	0.1046
$F(16, 533)$	4.7046	P-value(F)	5.84e–09

Granger causality F-tests of zero restriction

Null hypothesis:	F-Statistics:	p-value:
All lags of Δindp do not Granger cause Δlog_SP500.	7.3063	[0.0000]

”

Table 3, lag order 4

Equation 1: Δindp

	Coefficient	Std. Error	t-ratio	p-value
const	-0.0458	0.0428	-1.0701	0.2851
$\Delta\text{indp}_{(t-1)}$	0.0558	0.0867	0.6435	0.5202
$\Delta\text{indp}_{(t-2)}$	0.1379	0.0479	2.8775	0.0042
$\Delta\text{indp}_{(t-3)}$	0.2051	0.0527	3.8874	0.0001
$\Delta\text{indp}_{(t-4)}$	0.1224	0.0425	2.8787	0.0042
$\Delta\text{log\_will5000}_{(t-1)}$	0.6034	0.5512	1.0946	0.2742
$\Delta\text{log\_will5000}_{(t-2)}$	2.1210	0.7281	2.9128	0.0037
$\Delta\text{log\_will5000}_{(t-3)}$	2.7954	0.5560	5.0277	0.0000
$\Delta\text{log\_will5000}_{(t-4)}$	0.3877	0.5650	0.6862	0.4929
q_2	0.0367	0.0500	0.7342	0.4631
q_3	0.0356	0.0593	0.5999	0.5488
q_4	0.1421	0.0554	2.5626	0.0107
Δoil	0.0055	0.0106	0.5194	0.6037

Mean dependent var	0.1195	S.D. dependent var	0.5209
Sum squared resid	107.9769	S.E. of regression	0.4505
R^2	0.2687	Adjusted R^2	0.2522
$F(12, 532)$	13.5107	P-value(F)	1.62e–24

Granger causality F-tests of zero restriction

Null hypothesis:	F-Statistics:	p-value:
All lags of Δlog_will5000 do not Granger cause Δindp.	13.2357	[0.0000]

Table 3, lag order 4

Equation 2: Δlog_will5000

	Coefficient	Std. Error	t-ratio	p-value
const	0.0097	0.0037	2.5988	0.0096
$\Delta\text{indp}_{(t-1)}$	0.0045	0.0066	0.6904	0.4902
$\Delta\text{indp}_{(t-2)}$	0.0052	0.0034	1.5237	0.1282
$\Delta\text{indp}_{(t-3)}$	−0.0016	0.0036	−0.4572	0.6477
$\Delta\text{indp}_{(t-4)}$	−0.0070	0.0036	−1.9624	0.0502
$\Delta\text{log\_will5000}_{(t-1)}$	0.1948	0.0536	3.6353	0.0003
$\Delta\text{log\_will5000}_{(t-2)}$	−0.0781	0.0499	−1.5657	0.1180
$\Delta\text{log\_will5000}_{(t-3)}$	0.0415	0.0574	0.7236	0.4697
$\Delta\text{log\_will5000}_{(t-4)}$	−0.0061	0.0512	−0.1194	0.9050
q_2	−0.0016	0.0042	−0.3879	0.6982
q_3	−0.0096	0.0047	−2.0108	0.0449
q_4	−0.0009	0.0049	−0.1878	0.8511
Δoil	0.0016	0.0007	2.2159	0.0271

Mean dependent var	0.0081	S.D. dependent var	0.0401
Sum squared resid	0.7974	S.E. of regression	0.0387
R^2	0.0908	Adjusted R^2	0.0703
$F(12, 532)$	2.8338	P-value(F)	0.0008

Granger causality F-tests of zero restriction

Null hypothesis:	F-Statistics:	p-value:
All lags of Δindp do not Granger cause Δlog_will5000.	1.2218	[0.3005]

Table 4, lag order 2

Equation 1: Δmanifacturin

	Coefficient	Std. Error	t-ratio	p-value
const	-0.1924	0.2051	-0.9381	0.3486
Δmanifacturin$_{(t-1)}$	0.0379	0.0514	0.7386	0.4604
Δmanifacturin$_{(t-2)}$	0.1077	0.0495	2.1767	0.0299
Δlog_SP500$_{(t-1)}$	7.7188	2.9300	2.6344	0.0087
Δlog_SP500$_{(t-2)}$	7.3857	3.0856	2.3936	0.0170
q_2	0.0044	0.2665	0.0167	0.9866
q_3	0.1577	0.2876	0.5484	0.5837
q_4	0.2565	0.2696	0.9511	0.3420
Δoil	0.1055	0.0232	4.5422	0.0000

Mean dependent var	0.0118	S.D. dependent var	2.3266
Sum squared resid	2687.640	S.E. of regression	2.2288
R^2	0.0956	Adjusted R^2	0.0822
$F(8, 541)$	6.9773	P-value(F)	8.96e–09

Granger causality F-tests of zero restriction

Null hypothesis:	F-Statistics:	p-value:
All lags of Δlog_SP500 do not Granger cause Δmanifacturin.	7.12	[0.0009]

Table 4, lag order 2

Equation 2: Δlog_SP500

	Coefficient	Std. Error	t-ratio	p-value
const	0.0074	0.0031	2.3396	0.0197
Δmanifacturin$_{(t-1)}$	0.0000	0.0007	0.0096	0.9923
Δmanifacturin$_{(t-2)}$	0.0000	0.0006	−0.0253	0.9799
Δlog_SP500$_{(t-1)}$	0.2454	0.0480	5.1056	0.0000
Δlog_SP500$_{(t-2)}$	−0.0771	0.0506	−1.5218	0.1287
q_2	−0.0015	0.0039	−0.3936	0.6940
q_3	−0.0085	0.0044	−1.9135	0.0562
q_4	−0.0011	0.0043	−0.2748	0.7836
Δoil	0.0014	0.0008	1.7410	0.0823

Mean dependent var	0.0058	S.D. dependent var	0.0365
Sum squared resid	0.6652	S.E. of regression	0.03506
R^2	0.0942	Adjusted R^2	0.0809
$F(8, 541)$	5.0233	P-value(F)	4.96e–06

Granger causality F-tests of zero restriction

Null hypothesis:	F-Statistics:	p-value:
All lags of Δmanifacturin do not Granger cause Δlog_SP500.	0.0004	[0.9996]

Table 5 , lag order 2

Equation 1: Δnonmanifacturing

	Coefficient	Std. Error	t-ratio	p-value
const	−0.1460	0.2916	−0.5008	0.6170
Δnonmanifacturing$_{(t-1)}$	−0.3691	0.0678	−5.4368	0.0000
Δnonmanifacturing$_{(t-2)}$	−0.2620	0.0641	−4.0882	0.0001
Δlog_SP500$_{(t-1)}$	14.7809	4.0839	3.6193	0.0004
Δlog_SP500$_{(t-2)}$	2.1657	3.5969	0.6021	0.5477
q_2	−0.0385	0.3701	−0.1041	0.9172
q_3	0.4705	0.3902	1.2056	0.2293
q_4	−0.2040	0.3490	−0.5859	0.5586
Δoil	0.0585	0.0267	2.1939	0.0293

Mean dependent var	−0.0061	S.D. dependent var	1.9954
Sum squared resid	746.0194	S.E. of regression	1.8414
R^2	0.1782	Adjusted R^2	0.1483
$F(8, 220)$	5.1549	P-value(F)	6.61e–06

Granger causality F-tests of zero restriction

Null hypothesis:	F-Statistics:	p-value:
All lags of Δlog_SP500 do not Granger cause Δnonmanifacturing.	7.0489	[0.0011]

Table 5 , lag order 2

Equation 2: Δlog_SP500

	Coefficient	Std. Error	t-ratio	p-value
const	−0.0006	0.0050	−0.1241	0.9013
Δnonmanifacturing$_{(t-1)}$	0.0002	0.0012	0.1416	0.8875
Δnonmanifacturing$_{(t-2)}$	−0.0010	0.0014	−0.7455	0.4568
Δlog_SP500$_{(t-1)}$	0.1873	0.0705	2.6582	0.0084
Δlog_SP500$_{(t-2)}$	−0.0762	0.0724	−1.0531	0.2934
q_2	0.0039	0.0063	0.6295	0.5297
q_3	−0.0022	0.0072	−0.3199	0.7493
q_4	0.0122	0.0066	1.8368	0.0676
Δoil	0.0022	0.0009	2.4392	0.0155

Mean dependent var	0.0036	S.D. dependent var	0.0387
Sum squared resid	0.2891	S.E. of regression	0.0362
R^2	0.1563	Adjusted R^2	0.1256
$F(8, 220)$	3.4219	P-value(F)	0.0010

Granger causality F-tests of zero restriction

Null hypothesis:	F-Statistics:	p-value:
All lags of Δnonmanifacturing do not Granger cause Δlog_SP500.	0.4024	[0.6692]

”

Table 6, lag order 6

Equation 1: Δunemployment

	Coefficient	Std. Error	t-ratio	p-value
const	0.0153	0.0069	2.2225	0.0265
Δunemployment$_{(t-1)}$	0.0253	0.0415	0.6106	0.5417
Δunemployment$_{(t-2)}$	0.1734	0.0356	4.8668	0.0000
Δunemployment$_{(t-3)}$	0.0911	0.0402	2.2661	0.0237
Δunemployment$_{(t-4)}$	0.1007	0.0358	2.8122	0.0050
Δunemployment$_{(t-5)}$	0.0894	0.0350	2.5523	0.0109
Δunemployment$_{(t-6)}$	0.0486	0.0412	1.1813	0.2379
Δlog_SP500$_{(t-1)}$	−0.4341	0.1988	−2.1834	0.0293
Δlog_SP500$_{(t-2)}$	−0.2947	0.1994	−1.4781	0.1398
Δlog_SP500$_{(t-3)}$	−0.5423	0.2019	−2.6855	0.0074
Δlog_SP500$_{(t-4)}$	−0.5424	0.2152	−2.5199	0.0119
Δlog_SP500$_{(t-5)}$	−0.3026	0.1856	−1.6300	0.1035
Δlog_SP500$_{(t-6)}$	−0.4219	0.1740	−2.4247	0.0155
Δinflation_(t-1	0.0092	0.0272	0.3404	0.7336
Δinflation$_{(t-2)}$	0.0375	0.0183	2.0443	0.0413
Δinflation$_{(t-3)}$	−0.0203	0.0228	−0.8885	0.3746
Δinflation$_{(t-4)}$	−0.0090	0.0229	−0.3945	0.6933
Δinflation$_{(t-5)}$	0.0462	0.0226	2.0444	0.0413
Δinflation$_{(t-6)}$	−0.0212	0.0214	−0.9912	0.3219
Δoil	−0.0007	0.0018	−0.4196	0.6749

Mean dependent var	−0.0006	S.D. dependent var	0.1957
Sum squared resid	24.3294	S.E. of regression	0.1770
R^2	0.2009	Adjusted R^2	0.1814
$F(16, 776)$	9.4804	P-value(F)	4.78e–25

Granger causality F-tests of zero restriction

Null hypothesis:	F-Statistics:	p-value:
All lags of Δlog_SP500 do not Granger cause Δunemployment.	6.6109	[0.0000]

Table 6, lag order 6

Equation 2: Δlog_SP500

	Coefficient	Std. Error	t-ratio	p-value
const	0.0044	0.0013	3.3537	0.0008
Δunemployment$_{(t-1)}$	0.0144	0.0064	2.2450	0.0251
Δunemployment$_{(t-2)}$	−0.0123	0.0064	−1.9348	0.0534
Δunemployment$_{(t-3)}$	−0.0024	0.0059	−0.4144	0.6787
Δunemployment$_{(t-4)}$	0.0008	0.0065	0.1308	0.8960
Δunemployment$_{(t-5)}$	0.0104	0.0056	1.8577	0.0636
Δunemployment$_{(t-6)}$	0.0032	0.0066	0.4875	0.6261
Δlog_SP500$_{(t-1)}$	0.2506	0.0352	7.1070	0.0000
Δlog_SP500$_{(t-2)}$	−0.0745	0.0373	−1.9990	0.0460
Δlog_SP500$_{(t-3)}$	0.0492	0.0408	1.2046	0.2287
Δlog_SP500$_{(t-4)}$	0.0298	0.0420	0.7109	0.4773
Δlog_SP500$_{(t-5)}$	0.1060	0.0425	2.4919	0.0129
Δlog_SP500_(t-60	−0.1100	0.0478	−2.3015	0.0216
Δinflation$_{(t-1)}$	−0.0008	0.0038	−0.2226	0.8239
Δinflation$_{(t-2)}$	−0.0086	0.0045	−1.9166	0.0557
Δinflation$_{(t-3)}$	0.0037	0.0047	0.7914	0.4290
Δinflation$_{(t-4)}$	0.0010	0.0027	0.3682	0.7129
Δinflation_(t-50	−0.0025	0.0029	−0.8542	0.3932
Δinflation$_{(t-6)}$	0.0019	0.0029	0.6472	0.5177
Δoil	0.0013	0.0008	1.6478	0.0998

Mean dependent var	0.0059	S.D. dependent var	0.0349
Sum squared resid	0.8532	S.E. of regression	0.0331
R^2	0.1201	Adjusted R^2	0.0986
$F(19, 776)$	5.0618	P-value(F)	1.69e–11

Granger causality F-tests of zero restriction

Null hypothesis:	F-Statistics:	p-value:
All lags of Δunemployment do not Granger cause Δlog_SP500.	2.1885	[0.0422]

Table 6, lag order 6

Equation 3: Δinflation

	Coefficient	Std. Error	t-ratio	p-value
const	0.0085	0.0112	0.7594	0.4478
Δunemployment$_{(t-1)}$	−0.0075	0.0708	−0.1071	0.9147
Δunemployment$_{(t-2)}$	0.0551	0.0834	0.6613	0.5086
Δunemployment$_{(t-3)}$	−0.1807	0.0773	−2.3372	0.0197
Δunemployment$_{(t-4)}$	−0.1494	0.0796	−1.8762	0.0610
Δunemployment$_{(t-5)}$	−0.1238	0.0794	−1.5584	0.1196
Δunemployment$_{(t-6)}$	−0.0427	0.0705	−0.6052	0.5453
Δlog_SP500$_{(t-1)}$	−0.5428	0.3229	−1.6809	0.0932
Δlog_SP500$_{(t-2)}$	0.4686	0.3570	1.3126	0.1897
Δlog_SP500$_{(t-3)}$	−0.5018	0.3598	−1.3947	0.1635
Δlog_SP500$_{(t-4)}$	0.2277	0.4239	0.5373	0.5912
Δlog_SP500$_{(t-5)}$	−0.6243	0.3207	−1.9469	0.0519
Δlog_SP500$_{(t-6)}$	−0.3852	0.3306	−1.1654	0.2442
Δinflation$_{(t-1)}$	0.1791	0.1007	1.7778	0.0758
Δinflation$_{(t-2)}$	0.1448	0.0425	3.4002	0.0007
Δinflation$_{(t-3)}$	0.0336	0.0588	0.5715	0.5678
Δinflation$_{(t-4)}$	−0.0142	0.0403	−0.3536	0.7238
Δinflation$_{(t-5)}$	0.0372	0.0692	0.5387	0.5902
Δinflation$_{(t-6)}$	0.0365	0.0661	0.5527	0.5807
Δoil	0.0040	0.0015	2.6408	0.0084

Mean dependent var	0.0031	S.D. dependent var	0.3485
Sum squared resid	82.7917	S.E. of regression	0.3266
R^2	0.1429	Adjusted R^2	0.1219
$F(19, 776)$	4.9338	P-value(F)	4.14e–11

Granger causality F-tests of zero restriction

Null hypothesis:	F-Statistics:	p-value:
All lags of Δlog_SP500 do not Granger cause Δinflation.	1.5661	[0.1541]

Table 7, lag order 6

Equation 1: Δunemployment

	Coefficient	Std. Error	t-ratio	p-value
const	0.1800	0.0210	8.5636	0.0000
Δunemployment$_{(t-1)}$	−0.0634	0.0390	−1.6256	0.1044
Δunemployment$_{(t-2)}$	0.0869	0.0339	2.5600	0.0107
Δunemployment$_{(t-3)}$	0.0368	0.0387	0.9523	0.3412
Δunemployment$_{(t-4)}$	0.0648	0.0343	1.8858	0.0597
Δunemployment$_{(t-5)}$	0.0692	0.0340	2.0348	0.0422
Δunemployment$_{(t-6)}$	0.0313	0.0389	0.8046	0.4213
Δlog_SP500$_{(t-1)}$	−0.1918	0.1776	−1.0795	0.2807
Δlog_SP500$_{(t-2)}$	−0.0543	0.1934	−0.2811	0.7787
Δlog_SP500$_{(t-3)}$	−0.2387	0.1884	−1.2666	0.2057
Δlog_SP500$_{(t-4)}$	−0.3072	0.2037	−1.5080	0.1320
Δlog_SP500$_{(t-5)}$	−0.1253	0.1787	−0.7014	0.4833
Δlog_SP500$_{(t-6)}$	−0.2479	0.1552	−1.5970	0.1107
Δinflation$_{(t-1)}$	−0.0051	0.0258	−0.1986	0.8426
Δinflation$_{(t-2)}$	0.0247	0.0172	1.4349	0.1517
Δinflation$_{(t-3)}$	−0.0233	0.0220	−1.0600	0.2895
Δinflation$_{(t-4)}$	−0.0106	0.0217	−0.4915	0.6232
Δinflation$_{(t-5)}$	0.0424	0.0218	1.9397	0.0528
Δinflation$_{(t-6)}$	−0.0124	0.0207	−0.5968	0.5508
Δoil	−0.0006	0.0014	−0.3973	0.6913
d	−0.2046	0.0225	−9.0676	0.0000

Mean dependent var	−0.0006	S.D. dependent var	0.1957
Sum squared resid	21.9700	S.E. of regression	0.1683
R^2	0.2784	Adjusted R^2	0.2598
$F(20, 775)$	11.3683	P-value(F)	5.34e–32

Table 7, lag order 6

Equation 2: Δlog_SP500

	Coefficient	Std. Error	t-ratio	p-value
const	-0.0109	0.0049	-2.1963	0.0284
Δunemployment$_{(t-1)}$	0.0227	0.0065	3.4907	0.0005
Δunemployment$_{(t-2)}$	-0.0043	0.0070	-0.6119	0.5408
Δunemployment$_{(t-3)}$	0.0025	0.0056	0.4559	0.6486
Δunemployment$_{(t-4)}$	0.0042	0.0064	0.6507	0.5154
Δunemployment$_{(t-5)}$	0.0123	0.0055	2.2096	0.0274
Δunemployment$_{(t-6)}$	0.0048	0.0066	0.7294	0.4660
Δlog_SP500$_{(t-1)}$	0.2280	0.0378	6.0210	0.0000
Δlog_SP500$_{(t-2)}$	-0.0970	0.0373	-2.5981	0.0096
Δlog_SP500$_{(t-3)}$	0.0208	0.0404	0.5154	0.6064
Δlog_SP500$_{(t-4)}$	0.0079	0.0414	0.1909	0.8487
Δlog_SP500$_{(t-5)}$	0.0894	0.0431	2.0747	0.0383
Δlog_SP500$_{(t-6)}$	-0.1262	0.0470	-2.6821	0.0075
Δinflation$_{(t-1)}$	0.0005	0.0039	0.1237	0.9016
Δinflation$_{(t-2)}$	-0.0074	0.0044	-1.6584	0.0976
Δinflation$_{(t-3)}$	0.0040	0.0046	0.8628	0.3885
Δinflation$_{(t-4)}$	0.0011	0.0027	0.4272	0.6694
Δinflation$_{(t-5)}$	-0.0021	0.0029	-0.7539	0.4512
Δinflation$_{(t-6)}$	0.0010	0.0028	0.3729	0.7093
Δoil	0.0013	0.0007	1.7291	0.0842
d	0.0191	0.0056	3.3823	0.0008

Mean dependent var	0.0059	S.D. dependent var	0.0349
Sum squared resid	0.8326	S.E. of regression	0.0327
R^2	0.1413	Adjusted R^2	0.1191
$F(20, 775)$	5.6498	P-value(F)	7.85e–14

Table 7, lag order 6

Equation 3: Δinflation

	Coefficient	Std. Error	t-ratio	p-value
const	0.0490	0.0451	1.0855	0.2780
Δunemployment$_{(t-1)}$	−0.0294	0.0729	−0.4036	0.6866
Δunemployment$_{(t-2)}$	0.0338	0.0834	0.4061	0.6848
Δunemployment$_{(t-3)}$	−0.1941	0.0815	−2.3802	0.0175
Δunemployment$_{(t-4)}$	−0.1582	0.0809	−1.9556	0.0509
Δunemployment$_{(t-5)}$	−0.1288	0.0795	−1.6203	0.1056
Δunemployment$_{(t-6)}$	−0.0469	0.0694	−0.6759	0.4993
Δlog_SP500$_{(t-1)}$	−0.4832	0.3103	−1.5570	0.1199
Δlog_SP500$_{(t-2)}$	0.5277	0.3549	1.4869	0.1375
Δlog_SP500$_{(t-3)}$	−0.4271	0.3569	−1.1966	0.2318
Δlog_SP500$_{(t-4)}$	0.2856	0.4244	0.6730	0.5012
Δlog_SP500$_{(t-5)}$	−0.5807	0.3170	−1.8317	0.0674
Δlog_SP500$_{(t-6)}$	−0.3424	0.3270	−1.0470	0.2954
Δinflation$_{(t-1)}$	0.1755	0.1006	1.7438	0.0816
Δinflation$_{(t-2)}$	0.1416	0.0419	3.3761	0.0008
Δinflation$_{(t-3)}$	0.0328	0.0586	0.5604	0.5753
Δinflation$_{(t-4)}$	−0.0146	0.0405	−0.3624	0.7171
Δinflation$_{(t-5)}$	0.0363	0.0691	0.5252	0.5996
Δinflation$_{(t-6)}$	0.03874	0.0667	0.5805	0.5617
Δoil	0.0040	0.0015	2.6441	0.0084
d	−0.0503	0.0477	−1.0535	0.2924

Mean dependent var	0.0031	S.D. dependent var	0.3485
Sum squared resid	82.6489	S.E. of regression	0.3265
R^2	0.1444	Adjusted R^2	0.1223
$F(20, 775)$	4.6859	P-value(F)	9.12e–11

Table 8, lag order 6

Equation 1: Δunemployment

	Coefficient	Std. Error	t-ratio	p-value
const	0.0120	0.0092	1.3078	0.1923
$\Delta\text{unemployment}_{(t-1)}$	−0.0730	0.0757	−0.9648	0.3357
$\Delta\text{unemployment}_{(t-2)}$	0.1051	0.0631	1.6660	0.0971
$\Delta\text{unemployment}_{(t-3)}$	0.0428	0.0599	0.7140	0.4760
$\Delta\text{unemployment}_{(t-4)}$	−0.0115	0.0568	−0.2032	0.8392
$\Delta\text{unemployment}_{(t-5)}$	0.2064	0.0693	2.9784	0.0032
$\Delta\text{unemployment}_{(t-6)}$	0.1678	0.0766	2.1889	0.0296
$\Delta\text{log\_SP500}_{(t-1)}$	−0.4297	0.2456	−1.7493	0.0816
$\Delta\text{log\_SP500}_{(t-2)}$	−0.6189	0.2838	−2.1806	0.0303
$\Delta\text{log\_SP500}_{(t-3)}$	−0.3477	0.2775	−1.2528	0.2116
$\Delta\text{log\_SP500}_{(t-4)}$	−0.5560	0.2731	−2.0358	0.0430
$\Delta\text{log\_SP500}_{(t-5)}$	−0.2383	0.2481	−0.9604	0.3379
$\Delta\text{log\_SP500}_{(t-6)}$	−0.3611	0.2657	−1.3594	0.1754
$\Delta\text{inflation}_{(t-1)}$	−0.0320	0.0825	−0.3878	0.6985
$\Delta\text{inflation}_{(t-2)}$	−0.0006	0.0819	−0.0083	0.9934
$\Delta\text{inflation}_{(t-3)}$	−0.0377	0.0765	−0.4925	0.6229
$\Delta\text{inflation}_{(t-4)}$	−0.0460	0.0710	−0.6483	0.5175
$\Delta\text{inflation}_{(t-5)}$	−0.0716	0.0708	−1.0109	0.3132
$\Delta\text{inflation}_{(t-6)}$	−0.0863	0.0667	−1.2947	0.1968
Δoil	−0.0011	0.0020	−0.5643	0.5731

Mean dependent var	−0.0012	S.D. dependent var	0.1592
Sum squared resid	4.2348	S.E. of regression	0.1384
R^2	0.3045	Adjusted R^2	0.2447
$F(19, 221)$	4.5566	P-value(F)	9.87e–09

Granger causality F-tests of zero restriction

Null hypothesis:	F-Statistics:	p-value:
All lags of Δlog_SP500 do not Granger cause Δunemployment.	3.5962	[0.0020]

Table 8, lag order 6

Equation 2: Δlog_SP500

	Coefficient	Std. Error	t-ratio	p-value
const	0.0038	0.0025	1.4980	0.1356
Δunemployment$_{(t-1)}$	−0.0060	0.0174	−0.3447	0.7307
Δunemployment$_{(t-2)}$	−0.0406	0.0145	−2.8008	0.0055
Δunemployment$_{(t-3)}$	−0.0024	0.0155	−0.1598	0.8732
Δunemployment$_{(t-4)}$	−0.0085	0.0174	−0.4903	0.6244
Δunemployment$_{(t-5)}$	−0.0024	0.0151	−0.1587	0.8740
Δunemployment$_{(t-6)}$	0.0195	0.0155	1.2558	0.2105
Δlog_SP500$_{(t-1)}$	0.2171	0.0615	3.5287	0.0005
Δlog_SP500$_{(t-2)}$	−0.1403	0.0762	−1.8399	0.0671
Δlog_SP500$_{(t-3)}$	0.0930	0.0702	1.3241	0.1868
Δlog_SP500$_{(t-4)}$	0.0221	0.0741	0.2982	0.7659
Δlog_SP500$_{(t-5)}$	0.0955	0.0677	1.4097	0.1600
Δlog_SP500$_{(t-6)}$	−0.1691	0.0843	−2.0061	0.0461
Δinflation$_{(t-1)}$	−0.0182	0.0194	−0.9379	0.3493
Δinflation$_{(t-2)}$	−0.0108	0.0158	−0.6816	0.4962
Δinflation$_{(t-3)}$	0.0097	0.0224	0.4367	0.6628
Δinflation$_{(t-4)}$	−0.0032	0.0183	−0.1760	0.8604
Δinflation$_{(t-5)}$	0.0165	0.0190	0.8653	0.3878
Δinflation$_{(t-6)}$	−0.0197	0.0190	−1.0343	0.3021
Δoil	0.0018	0.0007	2.4627	0.0146

Mean dependent var	0.0047	S.D. dependent var	0.0387
Sum squared resid	0.2818	S.E. of regression	0.0357
R^2	0.2198	Adjusted R^2	0.1527
$F(19, 221)$	2.8028	P-value(F)	0.0001

Granger causality F-tests of zero restriction

Null hypothesis:	F-Statistics:	p-value:
All lags of Δunemployment do not Granger cause Δlog_SP500.	1.6505	[0.1345]

Table 8, lag order 6

Equation 3: Δinflation

	Coefficient	Std. Error	t-ratio	p-value
const	−0.0044	0.0080	−0.5481	0.5842
Δunemployment$_{(t-1)}$	0.0570	0.0550	1.0360	0.3013
Δunemployment$_{(t-2)}$	0.0437	0.0526	0.8310	0.4069
Δunemployment$_{(t-3)}$	−0.0179	0.0497	−0.3599	0.7193
Δunemployment$_{(t-4)}$	−0.0659	0.0602	−1.0941	0.2751
Δunemployment$_{(t-5)}$	−0.1107	0.0567	−1.9513	0.0523
Δunemployment$_{(t-6)}$	−0.0441	0.0551	−0.8006	0.4242
Δlog_SP500$_{(t-1)}$	−0.0360	0.2293	−0.1571	0.8753
Δlog_SP500$_{(t-2)}$	0.2368	0.2329	1.0168	0.3104
Δlog_SP500$_{(t-3)}$	−0.0957	0.2165	−0.4422	0.6588
Δlog_SP500$_{(t-4)}$	−0.0301	0.2157	−0.1399	0.8889
Δlog_SP500$_{(t-5)}$	0.2784	0.2136	1.3032	0.1939
Δlog_SP500$_{(t-6)}$	−0.0516	0.2773	−0.1862	0.8525
Δinflation$_{(t-1)}$	0.0694	0.0627	1.1067	0.2696
Δinflation$_{(t-2)}$	0.0235	0.0669	0.3512	0.7257
Δinflation$_{(t-3)}$	0.0802	0.0650	1.2338	0.2186
Δinflation$_{(t-4)}$	−0.0787	0.0658	−1.1955	0.2332
Δinflation$_{(t-5)}$	0.0602	0.0661	0.9099	0.3639
Δinflation$_{(t-6)}$	0.0543	0.0761	0.7136	0.4762
Δoil	0.0024	0.0015	1.5659	0.1188

Mean dependent var	−0.0024	S.D. dependent var	0.1227
Sum squared resid	3.2898	S.E. of regression	0.1220
R^2	0.0908	Adjusted R^2	0.0126
$F(19, 221)$	1.3073	P-value(F)	0.1801

Granger causality F-tests of zero restriction

Null hypothesis:	F-Statistics:	p-value:
All lags of Δlog_SP500 do not Granger cause Δinflation.	0.4939	[0.8125]

Table 9, lag order 6

Equation 1: Δunemployment

	Coefficient	Std. Error	t-ratio	p-value
const	0.0122	0.0093	1.3127	0.1906
Δunemployment$_{(t-1)}$	−0.0629	0.0761	−0.8267	0.4093
Δunemployment$_{(t-2)}$	0.1176	0.0611	1.9227	0.0558
Δunemployment$_{(t-3)}$	0.0514	0.0595	0.8648	0.3881
Δunemployment$_{(t-4)}$	−0.0037	0.0571	−0.0654	0.9479
Δunemployment$_{(t-5)}$	0.2151	0.0651	3.3042	0.0011
Δunemployment$_{(t-6)}$	0.1701	0.0710	2.3958	0.0174
Δlog_SP500$_{(t-1)}$	−0.4333	0.2418	−1.7917	0.0745
Δlog_SP500$_{(t-2)}$	−0.5971	0.2800	−2.1319	0.0341
Δlog_SP500$_{(t-3)}$	−0.3256	0.2817	−1.1557	0.2490
Δlog_SP500$_{(t-4)}$	−0.5067	0.2753	−1.8406	0.0670
Δlog_SP500$_{(t-5)}$	−0.2056	0.2488	−0.8264	0.4094
Δlog_SP500$_{(t-6)}$	−0.3613	0.2588	−1.3963	0.1640
Δoil	−0.0009	0.0019	−0.4610	0.6452

Mean dependent var	−0.0012	S.D. dependent var	0.1592
Sum squared resid	4.3064	S.E. of regression	0.1377
R^2	0.2928	Adjusted R^2	0.2523
$F(13, 227)$	6.2685	P-value(F)	4.69e–10

Granger causality F-tests of zero restriction

Null hypothesis:	F-Statistics:	p-value:
All lags of Δlog_SP500 do not Granger cause Δunemployment.	3.3985	[0.0031]

Table 9, lag order 6

Equation 2: Δlog_SP500

	Coefficient	Std. Error	t-ratio	p-value
const	0.0039	0.0025	1.5630	0.1194
Δunemployment$_{(t-1)}$	-0.0061	0.0170	-0.3584	0.7204
Δunemployment$_{(t-2)}$	-0.0424	0.0146	-2.8979	0.0041
Δunemployment$_{(t-3)}$	-0.0025	0.0158	-0.1631	0.8706
Δunemployment$_{(t-4)}$	-0.0088	0.0172	-0.5118	0.6093
Δunemployment$_{(t-5)}$	0.0013	0.0150	0.0878	0.9301
Δunemployment$_{(t-6)}$	0.0221	0.0152	1.4570	0.1465
Δlog_SP500$_{(t-1)}$	0.2178	0.0602	3.6185	0.0004
Δlog_SP500$_{(t-2)}$	-0.1400	0.0760	-1.8415	0.0669
Δlog_SP500$_{(t-3)}$	0.0857	0.0697	1.2302	0.2199
Δlog_SP500$_{(t-4)}$	0.0194	0.0726	0.2669	0.7898
Δlog_SP500$_{(t-5)}$	0.1041	0.0659	1.5790	0.1157
Δlog_SP500$_{(t-6)}$	-0.1736	0.0826	-2.1024	0.0366
Δoil	0.0018	0.0007	2.4547	0.0149

Mean dependent var	0.0048	S.D. dependent var	0.0387
Sum squared resid	0.2858	S.E. of regression	0.0354
R^2	0.2088	Adjusted R^2	0.1634
$F(13, 227)$	3.410	P-value(F)	0

Granger causality F-tests of zero restriction

Null hypothesis:	F-Statistics:	p-value:
All lags Δunemployment of do not Granger cause Δlog_SP500.	1.7494	[0.1106]

Table 10, lag order 6

Equation 1: Δunemployment

	Coefficient	Std. Error	t-ratio	p-value
const	0.0253	0.0114	2.2026	0.0279
Δunemployment$_{(t-1)}$	−0.0571	0.0456	−1.2525	0.2108
Δunemployment$_{(t-2)}$	0.1091	0.0380	2.8696	0.0042
Δunemployment$_{(t-3)}$	0.0567	0.0416	1.3619	0.1736
Δunemployment$_{(t-4)}$	0.0762	0.0348	2.1866	0.0291
Δunemployment$_{(t-5)}$	0.0943	0.0343	2.7489	0.0061
Δunemployment$_{(t-6)}$	0.0769	0.0424	1.8132	0.0702
Δindp$_{(t-1)}$	−0.0895	0.0184	−4.8618	0.0000
Δindp$_{(t-2)}$	−0.0394	0.0145	−2.7158	0.0068
Δindp$_{(t-3)}$	−0.0138	0.0150	−0.9179	0.3589
Δindp$_{(t-4)}$	−0.0116	0.0151	−0.7643	0.4449
Δindp$_{(t-5)}$	−0.0037	0.0144	−0.2576	0.7967
Δindp$_{(t-6)}$	0.0210	0.0152	1.3766	0.1691
Δlog_SP500$_{(t-1)}$	−0.4501	0.1988	−2.2642	0.0238
Δlog_SP500$_{(t-2)}$	−0.2660	0.1923	−1.3833	0.1670
Δlog_SP500$_{(t-3)}$	−0.3321	0.1936	−1.7150	0.0868
Δlog_SP500$_{(t-4)}$	−0.3358	0.2123	−1.5820	0.1141
Δlog_SP500$_{(t-5)}$	−0.216	0.1904	−1.1391	0.2550
Δlog_SP500$_{(t-6)}$	−0.2741	0.1805	−1.5190	0.1292
Δinflation$_{(t-1)}$	0.0120	0.0267	0.4487	0.6537
Δinflation$_{(t-2)}$	0.0384	0.0179	2.1384	0.0328
Δinflation$_{(t-3)}$	−0.0185	0.0230	−0.8057	0.4207
Δinflation$_{(t-4)}$	−0.0149	0.0222	−0.6739	0.5006
Δinflation$_{(t-5)}$	0.0386	0.0213	1.8104	0.0706
Δinflation$_{(t-6)}$	−0.0241	0.0208	−1.1596	0.2466
q_3	−0.0075	0.0156	−0.4794	0.6318
q_4	0.0028	0.0184	0.1515	0.8796
Δoil	0.0014	0.0016	0.8595	0.3903

Mean dependent var	-0.0006	S.D. dependent var	0.1957
Sum squared resid	22.9606	S.E. of regression	0.1730
R^2	0.2459	Adjusted R^2	0.2184
$F(28, 767)$	9.2377	P-value(F)	5.81e–33

Granager causality F-tests of zero restriction

Null hypothesis:	F-Statistics:	p-value:
All lags of Δlog_SP500 do not Granger cause Δunemployment.	3.9504	[0.0007]
All lags of Δindp do not Granger cause Δunemployment.	6.7969	[0.0000]

Table 10, lag order 6

Equation 2: Δindp

	Coefficient	Std. Error	t-ratio	p-value
const	−0.0140	0.0297	−0.4730	0.6363
Δunemployment$_{(t-1)}$	−0.2482	0.0914	−2.7130	0.0068
Δunemployment$_{(t-2)}$	−0.0303	0.0738	−0.4117	0.6807
Δunemployment$_{(t-3)}$	−0.0088	0.0787	−0.1120	0.9108
Δunemployment$_{(t-4)}$	0.1286	0.0840	1.5305	0.1263
Δunemployment$_{(t-5)}$	0.1650	0.0961	1.7164	0.0865
Δunemployment$_{(t-6)}$	−0.1143	0.0745	−1.5341	0.1254
Δindp$_{(t-1)}$	0.0643	0.0504	1.2760	0.2023
Δindp$_{(t-2)}$	0.0881	0.0376	2.3385	0.0196
Δindp$_{(t-3)}$	0.1375	0.0485	2.8317	0.0048
Δindp$_{(t-4)}$	0.1001	0.0526	1.9004	0.0578
Δindp$_{(t-5)}$	−0.0028	0.0354	−0.0795	0.9367
Δindp$_{(t-6)}$	0.0590	0.0306	1.9286	0.0541
Δlog_SP500$_{(t-1)}$	0.5140	0.4269	1.2040	0.2289
Δlog_SP500$_{(t-2)}$	2.2218	0.6799	3.2675	0.0011
Δlog_SP500$_{(t-3)}$	2.0143	0.4747	4.2426	0.0000
Δlog_SP500$_{(t-4)}$	0.4023	0.4836	0.8318	0.4058
Δlog_SP500$_{(t-5)}$	0.3361	0.4681	0.7180	0.4730
Δlog_SP500$_{(t-6)}$	0.7888	0.4087	1.9300	0.0540
Δinflation$_{(t-1)}$	0.0051	0.0360	0.1439	0.8856
Δinflation$_{(t-2)}$	−0.0190	0.0308	−0.6170	0.5374
Δinflation$_{(t-3)}$	−0.0246	0.0367	−0.6720	0.5018
Δinflation$_{(t-4)}$	−0.0535	0.0417	−1.2802	0.2009
Δinflation$_{(t-5)}$	−0.0099	0.0378	−0.2639	0.7919
Δinflation$_{(t-6)}$	−0.0382	0.0457	−0.8367	0.4030
q_3	0.0292	0.0422	0.6922	0.4890
q_4	0.1024	0.0425	2.4062	0.0164
Δoil	0.0076	0.0074	1.0219	0.3072

Mean dependent var	0.1105	S.D. dependent var	0.4623
Sum squared resid	125.0436	S.E. of regression	0.4037
R^2	0.2641	Adjusted R^2	0.2372
$F(28, 767)$	9.7974	P-value(F)	3.03e–35

Granager causality F-tests of zero restriction

Null hypothesis:	F-Statistics:	p-value:
All lags of Δlog_SP500 do not Granger cause Δindp.	7.0233	[0.0000]
All lags of Δunemployment do not Granger cause Δindp.	2.1042	[0.0507]

Table 10, lag order 6

Equation 3: Δlog_SP500

	Coefficient	Std. Error	t-ratio	p-value
const	0.0058	0.0025	2.2937	0.0221
Δunemployment$_{(t-1)}$	0.0202	0.0077	2.6337	0.0086
Δunemployment$_{(t-2)}$	−0.0079	0.0063	−1.2502	0.2116
Δunemployment$_{(t-3)}$	−0.0017	0.0062	−0.2845	0.7761
Δunemployment$_{(t-4)}$	0.0024	0.0069	0.3497	0.7267
Δunemployment$_{(t-5)}$	0.0138	0.0059	2.3373	0.0197
Δunemployment$_{(t-6)}$	0.0054	0.0072	0.7509	0.4530
Δindp$_{(t-1)}$	0.0053	0.0057	0.9417	0.3466
Δindp$_{(t-2)}$	0.0038	0.0036	1.0540	0.2922
Δindp$_{(t-3)}$	−0.0031	0.0030	−1.0361	0.3005
Δindp$_{(t-4)}$	−0.0011	0.0031	−0.3519	0.7250
Δindp$_{(t-5)}$	0.0015	0.0024	0.6452	0.5190
Δindp$_{(t-6)}$	0.0046	0.0033	1.4135	0.1579
Δlog_SP500$_{(t-1)}$	0.2472	0.0357	6.9105	0.0000
Δlog_SP500$_{(t-2)}$	−0.0709	0.0357	−1.9839	0.0476
Δlog_SP500$_{(t-3)}$	0.0369	0.0364	1.0120	0.3119
Δlog_SP500$_{(t-4)}$	0.0152	0.0371	0.4101	0.6819
Δlog_SP500$_{(t-5)}$	0.1113	0.0468	2.3768	0.0177
Δlog_SP500$_{(t-6)}$	−0.0996	0.0449	−2.2179	0.0269
Δinflation$_{(t-1)}$	−0.0005	0.0039	−0.1256	0.9001
Δinflation$_{(t-2)}$	−0.0084	0.0044	−1.8857	0.0597
Δinflation$_{(t-3)}$	0.0034	0.0046	0.7400	0.4595
Δinflation$_{(t-4)}$	0.0010	0.0027	0.3818	0.7027
Δinflation$_{(t-5)}$	−0.0019	0.0030	−0.6403	0.5221
Δinflation$_{(t-6)}$	0.0021	0.0030	0.6904	0.4902
q_3	−0.0061	0.0033	−1.8202	0.0691
q_4	−0.0001	0.0033	−0.0396	0.9684
Δoil	0.0013	0.0006	1.9492	0.0516

Mean dependent var	0.0059	S.D. dependent var	0.0349
Sum squared resid	0.8379	S.E. of regression	0.0330
R^2	0.1359	Adjusted R^2	0.1043
$F(28, 767)$	4.8936	P-value(F)	9.08e–15

Granager causality F-tests of zero restriction

Null hypothesis:	F-Statistics:	p-value:
All lags of Δunemployment do not Granger cause Δlog_SP500.	2.8759	[0.0089]
All lags of Δindp do not Granger cause Δlog_SP500.	0.7495	[0.6099]

Table 10, lag order 6

Equation 4: Δinflation

	Coefficient	Std. Error	t-ratio	p-value
const	0.0085	0.0243	0.3492	0.7270
Δunemployment$_{(t-1)}$	0.0182	0.0743	0.2450	0.8065
Δunemployment$_{(t-2)}$	0.0789	0.0851	0.9268	0.3543
Δunemployment$_{(t-3)}$	−0.1862	0.0818	−2.2753	0.0231
Δunemployment$_{(t-4)}$	−0.1753	0.0824	−2.1278	0.0337
Δunemployment$_{(t-5)}$	−0.1556	0.0832	−1.8694	0.0620
Δunemployment$_{(t-6)}$	−0.0595	0.0757	−0.7862	0.4320
Δindp$_{(t-1)}$	0.0253	0.0236	1.0739	0.2832
Δindp$_{(t-2)}$	0.0405	0.0210	1.9310	0.0538
Δindp$_{(t-3)}$	−0.0074	0.0220	−0.3377	0.7357
Δindp$_{(t-4)}$	−0.0102	0.0201	−0.5063	0.6128
Δindp$_{(t-5)}$	−0.0525	0.0251	−2.0875	0.0372
Δindp$_{(t-6)}$	0.0059	0.0262	0.2253	0.8218
Δlog_SP500$_{(t-1)}$	−0.5674	0.3292	−1.7245	0.0850
Δlog_SP500$_{(t-2)}$	0.4936	0.3708	1.3312	0.1835
Δlog_SP500$_{(t-3)}$	−0.5299	0.3509	−1.5100	0.1314
Δlog_SP500$_{(t-4)}$	0.1293	0.4393	0.2945	0.7685
Δlog_SP500$_{(t-5)}$	−0.7255	0.3444	−2.1065	0.0355
Δlog_SP500$_{(t-6)}$	−0.3570	0.3489	−1.0231	0.3066
Δinflation$_{(t-1)}$	0.1780	0.1012	1.7587	0.0790
Δinflation$_{(t-2)}$	0.1439	0.0420	3.4228	0.0007
Δinflation$_{(t-3)}$	0.0352	0.0583	0.6043	0.5458
Δinflation$_{(t-4)}$	−0.0126	0.0401	−0.3158	0.7522
Δinflation$_{(t-5)}$	0.0395	0.0692	0.5713	0.5680
Δinflation$_{(t-6)}$	0.0377	0.0662	0.5692	0.5694
q_3	0.0012	0.0346	0.0375	0.9701
q_4	0.0006	0.0304	0.0224	0.9822
Δoil	0.0032	0.0016	1.9345	0.0534

Mean dependent var	0.0031	S.D. dependent var	0.3485
Sum squared resid	82.274	S.E. of regression	0.3275
R^2	0.1483	Adjusted R^2	0.1172
$F(28, 767)$	3.8706	P-value(F)	1.60e–10

Granager causality F-tests of zero restriction

Null hypothesis:	F-Statistics:	p-value:
All lags of Δlog_SP500 do not Granger cause Δinflation.	1.6094	[0.1415]
All lags of Δunemployment do not Granger cause Δinflation.	1.7644	[0.1036]