Master's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Economics and Management
NTNU Business School

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The relationship between macroeconomic variables and Norwegian industries

A VAR, VECM, Forecast and Impulse Response Analysis

Master's thesis in Economics and Business Management
Supervisor: Stein Frydenberg
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Preface

This study is conducted as a final assignment to complete my master's degree in Economics and Business Administration at NTNU Business School.

This thesis study how macroeconomic variables impact industry portfolios in Norway. Based on monthly data in the period 1997-2016, one Vector Autoregression (VAR) model and nine Vector Error Correction Models (VECM) are created and discussed. 12-month out-of-sample forecasts are created for each industry, as well as Impulse Response Functions (IRF) graphing the industries' response to unexpected shocks in each macroeconomic variable.

Through conversations with a Norwegian foundation, we discussed how the current macroeconomic picture affected the financial markets. Different diversification strategies were discussed, where diversifying between industries was mentioned. After researching the topic, I found previous studies to cover the relations between macroeconomic variables and stock markets as a whole, but not individual industry returns in Norway. Thus, I wanted to contribute by analyzing this topic.

I want to thank my academic supervisor Stein Frydenberg for feedback and guidance throughout the semester. I would also like to thank Professor Sjur Westgaard for insightful discussions regarding the topic as well as additional support.

The content of this paper reflects my personal opinions and is not necessarily supported by NTNU Business School.

Trondheim

23.05.19

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Abstract

Portfolio managers have the option to diversify their investments to reduce risk exposure. One option is to diversify between industries. Many studies have looked at the relationship between macroeconomic variables and stock markets as a whole. However, for portfolio managers knowing how changes in the macroeconomic picture relate to individual industries can give greater insight and help with their diversification decisions.

This paper study the impact of macroeconomic variables on ten Norwegian industries in the period January 1997 to December 2016. Cointegrated equations, indicating long-run relations, are found between the variables and nine of the portfolios, where the multi-factor approach Vector Error Correction Model (VECM) captures these relations. No cointegrated relations are found between the variables and the Energy index, where only the short-run relations are captured using a Vector Autoregression (VAR) approach. Thus, one VAR and nine VEC models are created, one for each industry in combination with the following six macroeconomic variables; the consumer price index (CPI), term structure (TS), industrial production (IP), USD/NOK exchange rate (ND), oil price (OP) and the volatility index VIX. Based on the models, 12-month out-of-sample forecasts are created, as well as Impulse Response Functions (IRF) graphing the response of each industry to unexpected shocks in the six variables.

The results show different short- and long-run relations between the industries and the macroeconomic variables. The main results show positive short-run relations between TS and six of the industry portfolios, and negative long-run relations with TS and VIX for all, except the Utilities industry. The forecasts for each model are decent but miss monthly deviations. The majority of portfolios respond with a permanent, negative effect to unexpected shocks in TS and VIX. Shocks to IP and ND get the least response. For the other variables the industries respond differently. The differences between the industries in short- and long-run relationships and responses to shocks in the macroeconomic variables give portfolio managers diversification opportunities. By examining the relationships between macroeconomic factors and different Norwegian industries, this thesis fills a gap in the literature by addressing the importance of industry diversification and extending the current research on macroeconomic factors and the Norwegian market.

Sammendrag

Porteføljeforvaltere har mulighet til å diversifisere investeringene deres for å redusere risiko. En mulighet er å diversifisere mellom industrier. Mange studier har sett på forholdet mellom makroøkonomiske variabler og hele aksjemarkeder. Det å vite hvordan endringer i det makroøkonomiske bildet relaterer til individuelle industrier derimot, kan gi større innsikt for porteføljeforvaltere, samt hjelpe med deres diversifiseringsstrategi.

Denne oppgaven studerer påvirkningen makroøkonomiske variabler har på norske industrier i perioden januar 1997 til desember 2016. Kointegrerte forhold som indikerer langsiktige forhold er funnet mellom variablene og ni industrier, hvor en Vector Error Correction Model (VECM) vil fange opp disse forholdene. Ingen kointegrerte forhold er funnet mellom variablene og Energi indeksen, hvor kun de kortsiktige forholdene blir tolket ved hjelp av en Vector Autoregression (VAR) tilnærming. Dermed blir en VAR og ni VEC modeller laget, én for hver industri i kombinasjon med følgende seks makroøkonomiske variabler; konsumprisindeksen (CPI), rentekurven (TS), industriell produksjon (IP), USD/NOK valutakurs (ND), oljeprisen (OP) og volatilitetsindeksen VIX. Basert på modellene blir out-of-sample prognoser laget, samt Impulse Response Functions (IRF) som grafer responsen til hver industri basert på sjokk fra de seks variablene.

Resultatene viser ulike kort- og langsiktige forhold mellom industriene og de makroøkonomiske variablene. Hovedresultatene viser en positiv kortsiktig forhold mellom TS og seks av industriporteføljene, og negative langtidsforhold med TS og VIX for alle, med unntak av Utilities-industrien. Prognosene for hver modell er noe korrekt, men bommer på månedlige avvik. Majoriteten av porteføljene responderer med permanent, negativ effekt fra sjokk i TS og VIX. I tillegg får sjokk i IP og ND minst respons fra porteføljene. For de andre variablene responderer industriene forskjellig. Forskjellene mellom industriene i de kort- og langsiktige forholdene, samt responsene til sjokk i de makroøkonomiske variablene gir porteføljeforvaltere muligheten til å diversifisere. Ved å studere forholdene mellom makroøkonomiske variabler og forskjellige norske industrier bidrar denne oppgaven til eksisterende litteratur ved å adressere viktigheten av diversifisering mellom industrier, samt å utvide eksisterende studier av makroøkonomiske faktorer og det norske markedet.

Contents

List of Figures

List of Tables

Acronyms

ADF Augmented Dickey-Fuller.

AIC Akaike's Information Criterion.

CPI Consumer Price Index.

GICS The Global Industry Classification Standard.

GNP Gross National Product.

HQIC Hannan-Quinn Information Criterion.

IP Industrial Production.

IRF Impulse Response Function.

LGB Long Term Government Bond.

LR Likelihood Ratio.

ND USD/NOK Exchange Rate.

NOVIX The Norwegian Volatility Index.

OP Oil Price.

PP Phillip-Perron.

TS Term Structure.

VAR Vector Autoregression.

VECM Vector Error Correction Model.

VIX The CBOE Volatility Index.

1. Introduction

This thesis studies the impact of six macroeconomic variables on ten industry portfolios in Norway. Each industry portfolio index is combined with the macroeconomic variables to create either a Vector Autoregression (VAR) model or a Vector Error Correction Model (VECM). The models are used to create out-of-sample forecasts for the industry indices to test the models' ability to forecast. In addition, Impulse Response Functions (IRF) are generated based on each model to study the indices' response to shocks in the six macroeconomic variables.

Portfolio managers rebalance their investments according to the market situation. If the market is seen to be highly priced, then a strategy could be to increase the weight invested in the money market. If the opposite is true, more weights will be allocated in the capital market. Investors allocate based on risk and expected return, where diversification allows for reduced risk exposure. When investing in different assets that are not perfectly correlated, the goal is to reduce or eliminate unsystematic risk. One strategy within the capital markets could be to diversify between industries. Studies have found industry diversification to provide greater risk reduction than diversifying between countries (Cavaglia et al., 2000). With the increased importance of industry diversification, I believe insight into the relationship between the macroeconomic picture and different Norwegian industries would benefit portfolio managers. This study will fill this gap as previous studies on the Norwegian economic situation have focused on the Norwegian market as a whole, and not individual industries (see, e.g. Gjerde & Saettem, 1999).

'Beating' the market should not be possible according to the Efficient-Market Hypothesis (Malkiel & Fama, 1970). The hypothesis states that the market reflects all available information and only new information should influence it. There are three versions of the model; (1) 'weak form' where only historical information is incorporated in the prices, (2) 'semi-strong form' where all publicly available information is reflected, and (3) 'strong form' where inside information is included in asset prices. Despite the definition, there are different interpretations of what 'efficient' incorporates. Granger (1986) assumes that 'efficient markets' cannot predict changes to stock prices, stating that certain assets should not be cointegrated as market forces and government involvements force them together after a short-run divergent. However, Dwyer Jr & Wallace (1992) suggest an alternative interpretation stating that an efficient market has no arbitrage opportunities, where they show how cointegrated variables are consistent with this interpretation of market efficiency. This is the assumption used in this paper.

Many studies have been conducted on the relationship between macroeconomic variables and stock markets as a whole (see, e.g. Chen et al., 1986; Hamao, 1988; Mukherjee & Naka, 1995; Gjerde & Saettem, 1999). Variables analyzed include inflation and term structure as changes will influence discount rates in valuation models (Mukherjee & Naka, 1995). Also, industrial production is used as a proxy for real activity, which influences expected future cash flows (Chen et al., 1986). Since the Norwegian economy is dependant on oil Gjerde & Saettem (1999) include both the oil price and USD/NOK exchange rate to study their relations to the market. Lastly, the volatility index is not widely studied but can be used as a proxy for market risk or the market's expectations of future volatility (Whaley, 2000).

The assumption for this thesis is that industries respond differently to changes in the macroeconomic picture. Petersen & Strongin (1996) find durable-goods industries to be approximately three times more cyclical than nondurable-goods industries. A reason for this is that the cyclical industries provide goods that can be postponed purchased in recessionary periods, while non-cyclical industries provide necessities and public goods (Berman & Pfleeger, 1997). Thus, it seems like the durable-goods industries, such as Materials, IT and Consumer Discretionary (ConsDisc), have different relations to the macroeconomic variable than the nondurable-goods industries, such as Health Care, Utilities and Consumer Staples (ConsStapl).

This thesis contributes as a supplement to previous research regarding macroeconomic influence on markets, filling the gap of industry differences in Norway. The practical goal of this paper is to help portfolio managers and investors make informed decisions about their industry diversification regarding changes to the macroeconomy. By including various variables previously studied, and adding a variable of market risk, this thesis aims to fill the gap of macroeconomic influence on Norwegian industries. Thus, the research questions studied in this paper are:

1. Are there short- and long-run relations between macroeconomic variables and Norwegian industries?

2. Do Norwegian industries have different relationships with the macroeconomic variables?

3. Can macroeconomic variables forecast future values of industry indices in Norway?

4. How do Norwegian industries respond to shocks in macroeconomic variables?

Long-run relations are found between the macroeconomic variables and all the industries, except the Energy industry. The industries are found to have different short-run relations, and more similar long-run relations, with mainly the Utilities industry deviating from the others. The main results show positive short-run relations between TS and six of the industry portfolios and negative long-run relations with TS and VIX for all except the Utilities industry. The forecasts for each model are decent but miss monthly deviations. The IRF graphs correspond with short- and long-run results, except the Utilities industry where it responds similarly as the other industries. The majority of portfolios respond with a permanent negative effect to unexpected shocks in TS and VIX. Shocks to IP and ND get the least response from the portfolios. For the other variables the industries respond differently. The differences between industries in short- and long-run relationships and responses to shocks in the macroeconomic variables gives portfolio managers diversification opportunities.

This paper is organized as follows: The first section reviews previous relevant studies relating to stock returns, economic growth, and industry diversification. The second section describes the methods used in the analysis, namely the Vector Autoregression (VAR) Model, Vector Error Correction Model (VECM), out-of-sample Forecast, and the Impulse Response Function (IRF). The third section explains the variables included, why they are chosen, and their expectations, together with their descriptive statistics. The fourth section goes through the empirical work where the models are described and interpreted, the 12-month forecasts are discussed, and the IRF graphs analyzed. The final section discusses theoretical and practical implications, limitations, and future research before concluding.

2. Literature Review

Based on previous research, this paper has selected six macroeconomic variables to study in combination with Norwegian industries, where I am interested in studying their relationships. Studies show how macroeconomic variables influence stock markets as a whole, and it is, therefore, fair to say they will influence individual industry indices, however, not to what extent. This section review literature on the chosen variables in combination with stock markets and economic growth. In addition, the literature on country vs. industry diversification will be reviewed before I comment on this paper in the context of existing literature.

2.1. Existing Literature

Chen et al. (1986) is the first to study the impact of macroeconomic variables on stock markets. They study the validity of the Asset Pricing Theory through factor analysis on the US market. Their results show that industrial production, changes in the risk premium for bonds, and the term structure are significantly priced in the stock market. Hamao (1988) conducts similar research for the Japanese stock market where inflation, unanticipated changes in the risk premium, and unanticipated changes in the slope of term structure are found to have significant impact. Surprisingly they find the oil price and exchange rate not to be priced in the market even though their economy is highly dependant on international trade. Poon & Taylor (1991) study the UK market using a different approach. They implement two-stage regressions using the one-period-ahead residuals. Their results contradict Chen et al. (1986) findings, concluding with no effect of similar macroeconomic variables on the UK market. Poon & Taylor (1991) argue possible explanations of the different results to be that other macroeconomic variables are at play, or that Chen et al. (1986) use an inadequate method detecting pricing relationships, or both. Thus, it is not guaranteed that this study will get similar results as the method used differs from both these studies.

In addition to studying the macroeconomic impact on stock returns, studies have focused on the impact on economic growth. Through multiple regressions Chen (1991) finds lagged production growth rate, default premium, term premium, short-term interest rate, and market dividend-price ratio to influence recent and future economic growth in the U.S. market. Here, the growth of GNP and consumption is used as a proxy for the current health of the economy. He finds that a below average lagged production growth forecasts a higher future growth rate of GNP the next two to five quarters, which also implies a high expected excess market return. Also, above average term spread forecasts higher GNP growth for the next five quarters, while above average one-month T-bill rate forecasts lower growth.

Mukherjee & Naka (1995) study the Japanese stock market and macroeconomic variables using a cointegrated format. They find the variables to be cointegrated, meaning a long-term relation exists, and therefore use the VECM approach. They find exchange rate, industrial production, and money supply to have positive relationships with the Japanese stock market, while inflation has a negative relationship. The authors specify that the VAR approach does not incorporate potential long-term relations and may suffer from misspecification bias. Kwon & Shin (1999) also use a VECM to analyze macroeconomic variables and the Korean stock market. They find that the Korean stock market is sensitive to foreign exchange rates, the trade balance, the money supply, and the production index.

Gjerde & Saettem (1999) study macroeconomic variables and the Norwegian stock market. This is the closest study to this paper, however, they focus on the market as a whole and not individual industries. The VAR approach is used, implying no long-run relations, where their main focus is on the causal relationships between all the variables. They find that both stock returns and inflation are affected by real interest rate changes and that oil price and real activity affect stock returns. In addition, previous Norwegian master theses have explored the topic. Eliassen & Vik (2010) find that growth in the credit indicator, C2, relates positively to the Norwegian stock market, while both the interest spread and savings have an inverse relation. Rongved & Solberg (2018) find positive dynamic relations between the Norwegian stock market and the German stock market, measured by the Deutscher Aktien Index, and USD/NOK exchange rate, and negative relations between the stock market and the variables EUR/NOK exchange rate and unemployment rate.

Instead of focusing on a whole stock market, Barrows & Naka (1994) study the relationship between macroeconomic variables and hospitality stocks in the U.S. in the period 1965-1991. They use multiple regression, including the variables expected inflation rate, money supply (Ml), domestic consumption, term structure of interest rate, and industrial production. They find that the macroeconomic variables can explain the movement of restaurant stock returns to a greater extent than either the lodging or industrial sectors. Thus, they find differences between the industries in relation to the macroeconomic variables.

Kavussanos et al. (2002) also study individual industries, but on a global scale. They look at global industries and macroeconomic variables in the period 1987-1997. They employ a multi-factor time series model, including industrial production, inflation, oil prices, fluctuations in exchange rates against the US dollar, and a measure of credit risk. Their results suggest that macroeconomic news has different effects on different industries. The return of the world market portfolio is the most important factor in explaining the variation in international industry returns, while the macroeconomic variables marginally increase the explanatory power of the model.

Implied volatility indices have not previously been included as a macroeconomic variable. However, they have been studied in relation to the U.S. stock market. Giot (2005) find a negative relationship between the S&P 500 and NASDAQ-100 volatility indices, VIX and VXN, and returns of their respective indices. As it is not widely studied, I find it to be an interesting variable to include. It gives an indicator of market risk and is therefore of interest for portfolio managers.

Regarding portfolio diversification, studies have shown a shift in the importance of country versus industry diversification in global equity portfolios. Studies conducted before 2000 found country effects to be greater in portfolio selection than industry effects, however, recent studies have found the opposite. Cavaglia et al. (2000) find in their European focused study that diversifying between industries in a global equity portfolio results in greater risk reduction than diversifying between countries. Therefore, this study could be of greater interest today than 20 years ago.

2.2. This Paper in the Context of Existing Literature

By examining the relationships between the macroeconomic picture and different Norwegian industries, this thesis fills a gap in the literature by (1) addressing the importance of industry diversification and (2) extending the current research on macroeconomic factors and returns. First, following the study of Cavaglia et al. (2000) finding industry diversification to provide greater risk reduction than diversifying between countries, this thesis focus on the industry related diversification opportunities in Norway. Previous studies have focused on global industries or a few industries within an economy, while this study looks at all industries in the economy. This makes it possible to see if the industries move differently and if any follows the stock market more closely using results from previous studies.

Secondly, this thesis contributes as a supplement to previous research on macroeconomic influence on stock markets, especially the work of Gjerde & Saettem (1999) studying the Norwegian stock market as a whole. In contrast to their study, this thesis uses the VECM approach in nine of ten models as cointegrated equations are found. Thus, long-run relations can be interpreted. The lengths of our samples are similar, including 20 years, however this thesis study more recent data. Lastly, an additional variable not widely studied in relation to macroeconomic studies is added, namely the volatility index VIX, used as a proxy for market risk.

3. Method

The goal of this paper is to study if industry portfolios can be explained by current and past values of macroeconomic variables. Chen et al. (1986) argues all variables influencing the market to be endogenous as only supernovas, earthquakes, and similar are truly exogenous. Similarly, all variables in this study are considered to be endogenous, where all influence each other. Either a VAR or VECM approach is used to study these relationships. Before running either approach, the individual variables are tested for stationarity. Then each model is tested for cointegration, where the results determine the approach. The number of lags included in each model is found before running a VAR or VECM. After each model is run their respective forecasts and IRF graphs are created. This section explains these processes in greater detail.

3.1. Stationarity

Variables integrated of order zero, I(0), are stationary and contains a systematic trend that is predictable. Problems that might occur if variables are not stationary include spurious regressions and t-ratios not following t-distribution. A variable, y_t, is stationary if:

- $E[y_t]$ is finite and independent of t
- $Var[y_t]$ is finite and independent of t
- $Cov[y_t, y_s]$ is a finite function of $|t-s|$ but not of t and s alone

Unit root tests are used to test for stationarity where H_0 = the variable contains a unit root, or ρ=1, and H_1 = the variable is generated by a stationary process. VAR models assume that all variables are stationary, I(0). In VEC models the stationarity is important to show cointegration between variables, where cointegration exists if the variables are I(1), namely stationary of the first order. This study uses the Augmented Dickey-Fuller (ADF) and Phillip-Perron (PP) tests to check for stationarity.

The Augmented Dickey-Fuller Test

The Dickey-Fuller Test developed by Dickey & Fuller (1979) is based on linear regression. However, since serial correlation is likely to be an issue the Augmented Dickey-Fuller (ADF) was developed which handles bigger models. The true model is assumed to be:

$$y_t = \alpha + y_{t-1} + u_t$$

where u_t is an independent and identically distributed zero-mean error term. The ADF then include the lags of the First Difference of the variable y_t, and fits the model:

$$\Delta y_t = \alpha + \beta y_{t-1} + \delta t + \zeta_1 \Delta y_{t-1} + \zeta_2 \Delta y_{t-2} + ... + \zeta_k \Delta y_{t-k} + \epsilon_t$$

where α is a constant term, δt is a time trend, and k is the number of lags selected. Testing for $\beta = 0$ is the same as testing if y_t follows a unit root process, or $\rho = 1$. Selecting appropriate number of lags is important as too few lags might lead to over-rejecting the null hypothesis when it is true, and too many lags could reduce the power of the test (Maysami et al., 2004). The t-statistic is used to test the null hypothesis.

Phillip-Perron Test

This unit root test is a modified Dickey-Fuller test. The test statistics are calculated from the results of fitting the model:

$$y_t = \alpha + \rho y_{t-1} + \delta t + u_t$$

where α, ρ, δt, and u_t are as descibed above. The Phillip-Perron test is considered more robust than the ADF as it corrects for autocorrelation and heteroscedasticity in the errors.

3.2. Cointegration

The models are tested for cointegration to determine whether to analyze using a VAR or VEC approach. Cointegration between two variables exists if each variable is an I(1) process, meaning the variables in Levels are not stationary, but a linear combination of them is. If cointegrated equations exist, there is a long-run causal relationship between the variables and the VECM fits best for further analysis, if not the VAR approach is used. Engle & Granger (1987) introduces cointegration tests for bivariate models. However, this study uses the Johansen test for cointegration as described by Johansen (1988) as each model includes seven variables. The null hypothesis says there are no more than r cointegrated relations. The hypothesis is rejected if the trace statistic is lower than the

Critical Value. The trace statistics is defined as:

$$\lambda_{trace} = -T \sum_{i=r+1}^{K} \ln(1-\widehat{\lambda}_i)$$

where T is the number of observations, K is the number of I(1) variables, r is the number of cointegrated equations, and $\widehat{\lambda}_i$ is the estimated eigenvalues. The test process starts by checking if zero cointegrations exist, or $r = 0$. If rejected, the test checks if one cointegration or less exist, or $r \leq 1$, and so on until the null hypothesis is accepted. It is possible to test for cointegration using the maximum-eigenvalue statistic defined as $\lambda_{max} = -T\ln(1-\widehat{\lambda}_{r+1})$. However, Cheung & Lai (1993) find the trace statistic to be more robust. Therefore, this thesis uses the trace statistics.

3.3. Lag Selection

As part of fitting a VAR or VEC model, a number of lags are selected. The selection of p-lags is based on a comparing the LR-statistics and the information criterion tests Akaike's Information Criterion (AIC) and Hannan-Quinn Information Criterion (HQIC):

$$LR(p) = 2\{LL(p) - LL(p-1)\}$$

$$AIC = -2\left(\frac{LL}{T}\right) + \frac{2t_p}{T}$$

$$HQIC = -2\left(\frac{LL}{T}\right) + \frac{2\ln\{ln(T)\}}{T}t_p$$

where p is the number of lags, t_p is the number of parameters in the model, T is number of observations, and LL is the log likelihood function for the model. The LL estimate is based on Hamilton (1994, 295-296):

$$LL = \left(\frac{T}{2}\right)\left\{\ln\left(|\widehat{\Sigma}^{-1}|\right) - K\ln(2\pi) - K\right\}$$

where $\widehat{\Sigma}$ is the maximum likelihood estimate of $E[\mathbf{u}_t\mathbf{u}_t']$, where $\mathbf{u}_t$ is the $K \times 1$ vector of disturbances, and K is the number of equations. Liew (2004) finds HQIC to be superior to find optimal lag length when the sample size is greater than 120. However, if the residuals are autocorrelated at the lag length selected by HQIC, different lags will be tested.

3.4. Vector Autoregressive Model

A Vector Autoregressive Model (VAR) model is used to explain the variables at time t based on their joint history described by p number of lags. The models are especially convenient for estimation and forecasting, and became popular after Sims (1980) influential work analyzing the dynamics of economic systems (Hamilton, 1994). To explain the model we look at a first order VAR model, VAR(1), with two variables, y_1 and y_2:

$$y_{1,t} = v_1 + \theta_{11} y_{1,t-1} + \theta_{12} y_{2,t-1} + u_{1t}$$

$$y_{2,t} = v_2 + \theta_{21} y_{1,t-1} + \theta_{22} y_{2,t-1} + u_{2t}$$

After the stacking the equations we get a general expression, y_t:

$$\underbrace{\begin{pmatrix} y_{1,t} \\ y_{2,t} \end{pmatrix}}_{y_t} = \underbrace{\begin{pmatrix} v_1 \\ v_2 \end{pmatrix}}_{v} + \underbrace{\begin{pmatrix} \theta_{11} & \theta_{12} \\ \theta_{21} & \theta_{22} \end{pmatrix}}_{A_1} \underbrace{\begin{pmatrix} y_{1,t-1} \\ y_{2,t-1} \end{pmatrix}}_{y_{t-1}} + \underbrace{\begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix}}_{u_t}$$

where y_t is a K-vector (here K=2) of variables, v is a K-vector of intercepts, and A_1 is a $K \times K$-matrix of coefficients showing the short-run relations between variables in the K-equations and p-lags. u_t is a K-vector of error terms assumed to be white noise, namely $E(u_t) = 0$, $E(u_t u_t') = \Sigma$, and $E(u_t u_s') = 0$ for $t \neq s$. Thus, a VAR(p) model can be written as:

$$y_t = v + A_1 y_{t-1} + A_2 y_{t-2} + \ldots + A_p y_{t-p} + u_t \tag{1}$$

3.5. Vector Error Correction Model

If variables are cointegrated, a Vector Error Correction Model (VECM) is used. Engle & Granger (1987) developed the key concepts of error correction models. A VECM adds an error correction term to the VAR model. The VAR model expressed in Equation 1 can be rewritten to VECM form:

$$\Delta y_t = v + \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + u_t \tag{2}$$

where y_t is a K-vector of I(1) variables, $\Pi = \sum_{j=1}^{j=p} A_j - \mathbf{I}_k$, $\Gamma_i = -\sum_{j=i+1}^{j=p} A_j$, and v and u_t are as described above.

If the variables A_t are I(1) Engle & Granger (1987) show that the matrix Π have rank $0 \leq r < K$. For a VECM Π has rank $0 < r < K$, meaning there is at least one cointegrated vector. Then Π can be expressed as $\Pi = \alpha\beta'$, where α and β are $r \times K$ matrices of rank r. α can be interpreted as the adjustment coefficients in the model, giving insight into how fast the variables adjust if in disequilibrium. A disequilibrium occurs if agents are not able to adjust to new information instantly due to the costs of adjustment (Maysami et al., 2004). Next, β includes the parameters in the cointegrating equations. Thus, if cointegrated, there exist linear combinations of $\beta' y_t$ that are stationary, even though y_t is not stationary. A VAR model excludes $\alpha\beta' y_t$, missing the long-term relationships.

3.6. Forecast

Based on VAR and VEC models it is possible to evaluate the models ability to predict future values of selected variables. From Equation 1 Lütkepohl (2005, 204-205) explain the optimal h-step forecast of y_{t-1} to be:

$$y_t(h) = \widehat{v} + \widehat{A}_1 y_t(h-1) + ... + \widehat{A}_p y_t(h-p)$$

where $y_t(j) := y_{t+j}$ for $j \leq 0$. Further, Lütkepohl (2005) assumes that forecasting and parameter estimation are based on independent processes with identical stochastic structure. Then the asymptotic estimator of the covariance matrix of the prediction error is:

$$\widehat{\Sigma}_{\widehat{y}}(h) = \widehat{\Sigma}_y(h) + \frac{1}{T}\widehat{\Omega}(h)$$

where $\widehat{\Sigma}_y(h)$ is the estimated mean square error (MSE) matrix of the forecast arising from unseen innovations, and $T^{-1}\widehat{\Omega}(h)$ estimates the error in the forecast that is due to using estimated, not true, coefficients. When the sample size grows, $T \to \infty$, and $T^{-1}\widehat{\Omega}(h) \to 0$ as the uncertainty to the coefficient estimates decreases. Thus, an estimator of $\widehat{\Sigma}_{\widehat{y}}(h)$ can be obtained by simply replacing the unknown quantities in $\widehat{\Sigma}_y(h)$ with estimators (Lütkepohl, 2005).

Forecasting 'out-of-sample' means using a model to predict a period that is not included in the model. Using this study as an example, the models are based on data in the period 1997-2016 and predictions are made for 2017. This makes it possible to compare with actual observed values in order to evaluate the models' forecasting abilities. In contrast, for an in-sample forecast the data for the forecasting period would be included and influenced the model.

3.7. Impulse Response Function

The Impulse Response Function (IRF) shows the response in variable y_1 by a shock in its own variable or another variable y_2. In a stationary VAR, the effects of shocks fade over time. In a VECM, however, the effects often remain because I(1) variables are not mean reverting, resulting in permanent shocks. Lütkepohl (2005, 51-52) illustrates the IRF assuming the following VAR model:

$$y_t = A_1 y_{t-1} + u_t$$

We set

$$A_1 = \begin{bmatrix} \mathrm{a} & \mathrm{c} \\ \mathrm{b} & \mathrm{d} \end{bmatrix}$$

With two variables y_1 and y_2 we get:

$$\begin{bmatrix} y_{1,t} \\ y_{2,t} \end{bmatrix} = \begin{bmatrix} \mathrm{a} & \mathrm{c} \\ \mathrm{b} & \mathrm{d} \end{bmatrix} \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \end{bmatrix} + \begin{bmatrix} u_{1,t} \\ u_{2,t} \end{bmatrix}$$

Tracing a unit shock in the first variable in period t = 0 gives:

$$y_0 = \begin{bmatrix} y_{1,0} \\ y_{2,0} \end{bmatrix} = \begin{bmatrix} u_{1,0} \\ u_{2,0} \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

$$y_1 = \begin{bmatrix} y_{1,1} \\ y_{2,1} \end{bmatrix} = A_1 y_0 = \begin{bmatrix} \mathrm{a} \\ 0 \end{bmatrix}$$

$$y_2 = \begin{bmatrix} y_{1,2} \\ y_{2,2} \end{bmatrix} = A_1 y_1 = A_1^2 y_0 = \begin{bmatrix} \mathrm{a}^2 + \mathrm{bc} \\ \mathrm{ab} + \mathrm{bd} \end{bmatrix}$$

Thus, continuing the process shows that $y_i = (y_{1,i}, y_{2,i})'$ is the first column of A_1^i. Lütkepohl (2005, 51-52) explains that a unit shock in y_{2t} at t =0 after i period result in a vector y_i which is the effect of the second column of A_1^i. Therefore, the effects of unit shocks to variables in a model after i periods are represented by the elements of A_1^i.

3.8. Diagnostics Tests

To check the reliability of VAR and VEC models diagnostics tests are run checking (1) if the residuals are autocorrelated, (2) whether the model is stable, and (3) if the disturbances are normally distributed.

First, the Lagrange-Multiplier Test is applied with the null hypothesis equalling no autocorrelation in lag j. As discussed in Johansen (1995, 21-22) the test regresses the estimated residuals from Equation 1 on the residual lagged s as well as the regressors in the model. The LM test statistics is:

$$LM_s = (T - pk - m - p - 0.5)\log\frac{|\widetilde{\Sigma}|}{|\widehat{\Sigma}|}$$

where T is number of observations, k is the lag length, $\widehat{\Sigma}$ is the variance estimate from Equation 1, and $\widetilde{\Sigma}$ is the estimate from the additional regression. The test statistics is asymptotically distributed as χ^2 with degrees of freedom given by $f = p^2$ (Johansen, 1995).

Secondly, a stability test is run to check if the models are stable. A VAR assumes stationarity, as desribed earlier, but also stability. A stable VAR is invertible and has a vector moving-average representation, giving forecast and IRFs known interpretations (Lütkepohl, 2005). The stability condition as described by Lütkepohl (2005) is:

$$\det(I_K - A_1 z - \ldots - A_p z^p) \neq 0 \quad \text{for } |z| \leq 1$$

where the companion matrix, A, is:

$$A = \begin{pmatrix} \mathrm{A}_1 & \mathrm{A}_2 & \ldots & \mathrm{A}_{p-1} & \mathrm{A}_p \\ \mathrm{I}_K & 0 & \ldots & 0 & 0 \\ 0 & \mathrm{I}_K & \ldots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \vdots & \mathrm{I}_K & 0 \end{pmatrix}$$

$$(K_p \times K_p)$$

Lütkepohl (2005) explains the *modulus* of a complex number $z = z_1 + iz_2$ is used, where z_1 and z_2 are the real and imaginary parts of z, respectively, and $i = \sqrt{-1}$. Further, the modulus of z is defined as $|z| := \sqrt{z_1^2 + z_2^2}$. Lütkepohl (2005) shows that a model is stable if the modulus of each eigenvalue of A is strictly less than one.

In a VECM the eigenvalue stability condition is tested to check if the number of cointegrated equations is misspecified, or if the assumed stationary variables are not stationary. The coefficient estimates from the VECM are used to estimate the coefficients of a corresponding VAR and then compute the eigenvalues of the companion matrix. A VECM model with K endogenous variables and r cointegrated relationships will have $K - r$ unit eigenvalues in the companion matrix. The remaining r eigenvalues should be less than 1 to have a stable model that converges towards its long-term equilibrium.

Finally, the Jarque-Bera statistic is used to determine if the disturbances of a model are normally distributed. The statistic is a combination of the skewness and kurtosis statistics (see Lütkepohl, 2005, 174-181, for detailed derivations of the statistics). Both the individual equations and the models as a whole are tested. The null hypothesis for the individual equations states that the disturbance of the equation is normally distributed. For the whole model, the null hypothesis states that all K disturbances have a K-dimensional multivariate normal distribution.

4. Data

Ten industry portfolios are studied in the period January 1997 to December 2016, consisting of 239 monthly observations. The period is chosen based on the availability of the industry portfolios, but I find 19 years to be sufficient for this analysis. Monthly data are studied as the consumer price index and industrial production are announced monthly. All the macroeconomic variables are collected using Macrobond, The Central Bank of Norway, and Statistics Norway. Both the consumer price index and industrial production are seasonally adjusted to remove seasonal patterns. Macrobond uses the X-13-ARIMA-SEATS program from the US Census Bureau, while Statistics Norway use the earlier version X-12-ARIMA approach (see Macrobond (2019) and SSB (2019) for more information). I find the data to be valid as it is compared using three different sources. Table 1 gives short descriptions of the variables used in the analysis. The natural logarithm of each variable is used in the analysis to avoid big outliers and to fit the data for this analysis as done by Mukherjee & Naka (1995). Further descriptions of the variables, why they are chosen, and their expected relation to the industries are explained next.

4.1. Descriptions and Expectations

Industry Portfolios

Returns of ten industry portfolios are collected from Ødegaard (2018) who constructs ten value-weighted and equally-weighted industry portfolios from Oslo Stock Exchange by categorizing stocks according to The Global Industry Classification Standard (GICS). A description of industry groups included in each industry portfolio is explained in Table A1 in the Appendix. The number of companies included in each portfolio ranges from 10 to 55. Based on the available industries of Ødegaard (2018) the industry portfolio indices studied are (1) Energy, (2) Materials, (3) Industrials, (4) Consumer Discretionary (ConsDisc), (5) Consumer Staples (ConsStapl), (6) Health Care, (7) Financials, (8) IT, (9) Telecom and (10) Utilities. This analysis uses the value-weighted portfolios similar to Gjerde & Saettem (1999), where the returns are weighted by the equity size of the firms. To conduct the analysis, the monthly returns are converted into indices with start value set to 100. As 35% of the Oslo Stock Exchange All-Share Index (OSEAX) consist of companies in the Energy industry it is expected that this industry has similar results as the Norwegian stock market

Table 1: Descriptions of Variables

Symbol	Variable	Definition
II_t	Industry Index	Indices created for each industry with start value = 100 and monthly returns as collected from Ødegaard (2018)
CPI_t	Consumer Price Index	$CPI_t = CPI_{t-1}$
TS_t	Term Structure	$LGB_t - NIBOR_t$
IP_t	Industrial Production	$IP_t = IP_{t-1}$
ND_t	USD/NOK Exchange Rate	Monthly average of USD/NOK exchange rate
OP_t	Oil Price	Monthly average of Crude Brent spot price in USD
VIX_t	Volatility Index	Monthly average of Chicago Board Options Exchange Volatility Index
Time Series Transformations		
ΔII_t	$= log[II_t/II_{t-1}]$	Return of industry index
ΔCPI_t	$= log[CPI_t/CPI_{t-1}]$	Realized inflation rate
ΔTS_t	$= log[TS_t/TS_{t-1}]$	Changes in term structure
ΔIP_t	$= log[IP_t/IP_{t-1}]$	Growth rate of industrial production
ΔND_t	$= log[ND_t/ND_{t-1}]$	Changes in exchange rate
ΔOP_t	$= log[OP_t/OP_{t-1}]$	Changes in oil price
ΔVIX_t	$= log[VIX_t/VIX_{t-1}]$	Changes in VIX

Description of variables in Levels and First Difference. LGB = Long Term Government Bond.

as studied by Gjerde & Saettem (1999) (see Appendix A.1). The nondurable-goods industries such as the Health Care, Utilities, and ConsStapl are expected to be more independent from the market since they are less cyclical. Thus, I expect them to differ from previous studies, as they might not react similarly to changes in the macroeconomic picture as the market.

CPI - Consumer Price Index

The Consumer Price Index (CPI) is used as a proxy for inflation. I expect there to be a negative relation between CPI and all industry returns. When inflation increases, nominal risk-free interest rate increases, thus higher discount rates in valuation models. If cash flows rise with inflation, this would be neutralized, but this is not always the case (Mukherjee & Naka, 1995). This is supported by the findings of Chen et al. (1986), and Mukherjee & Naka (1995). Similar to Chen (1991) and Gjerde & Saettem (1999), the lagged variable of CPI and IP are used since the announcement of inflation and production numbers account for the previous month.

TS - Term Structure

The Term Structure (TS) is an indicator of future interest rates. The Term Structure is constructed by subtracting the three-month NIBOR from the Norwegian ten-year government bond yield (LGB). A positive and increasing TS signals a future increase in interest rates. An increase in the short-run interest rate would influence the market negatively, as it affects valuation models. Thus, I expect a negative relationship between TS and all industries, as all company valuations would be affected by changes to the interest rates. Gjerde & Saettem (1999) find an initial positive response from the market to shocks in the NIBOR, while Eliassen & Vik (2010) find a negative relationship between TS and the Norwegian stock market. Also, Chen et al. (1986), Hamao (1988) and Chen (1991) find term structure to influence the stock market and economic growth.

IP - Industrial Production

Industrial Production (IP) is a measure of output in oil and gas extraction, manufacturing, mining & quarrying, and electricity supply (SSB, 2019). IP is a proxy for real activity which affects expected future cash flows. Therefore, I expect a positive relationship between IP and the industry indices. This is supported by the findings of Chen et al. (1986), Hamao (1988) and Mukherjee & Naka (1995). In addition, Chen (1991) find lagged production growth to be an indicator of recent and future economic growth. As mentioned, the lagged value of IP is used.

ND - Exchange rate

Similarly to Gjerde & Saettem (1999), the USD/NOK exchange rate (ND) is included. This makes it possible to compare the industries' relation to ND with the Norwegian market's relation. As 63.6% of Norwegian imports come from Europe, the EUR/NOK exchange rate is also relevant for this study (StatisticsNorway, 2018). However, as six variables already are included, I leave this for further research. I expect a positive relationship between ND and industries highly dependant on exports. When the NOK weakens compared to the USD, Norwegian products become cheaper. If the demand for these products is elastic, the export should increase, causing an increase in cash flows. This is supported by the findings of Mukherjee & Naka (1995). The monthly average of the exchange rate is used.

OP - Oil Price

In addition to being a common variable used in related studies (e.g. Chen et al., 1986; Gjerde & Saettem, 1999; Kavussanos et al., 2002), the oil price is appropriate to include in a Norwegian study as crude oil and natural gas amount to approximately half of Norway's total export (NorwegianPetroleum, 2019). Therefore, I expect a positive relationship between OP and all industries, especially the Energy industry as it is dependant on the oil price. This is supported by Gjerde & Saettem (1999) who find the stock market to react positively to changes in the oil price. OP is the monthly average of Crude Brent spot price in USD.

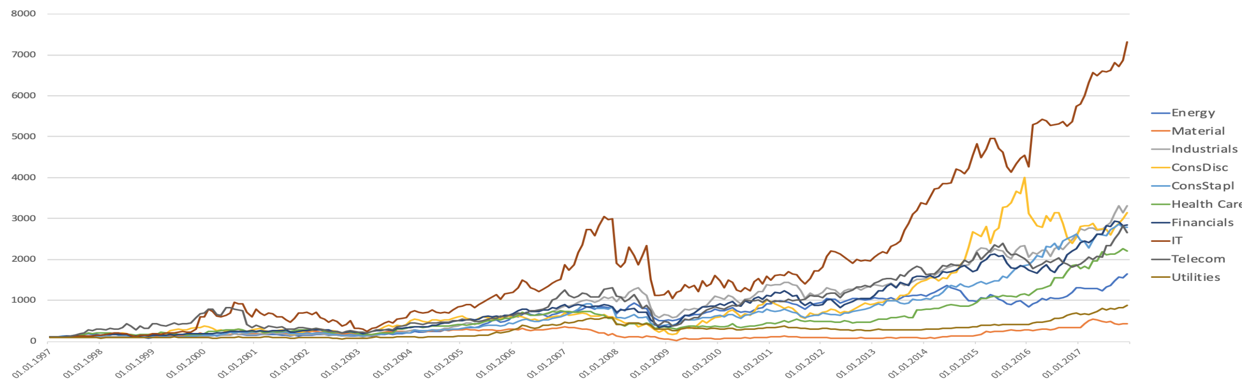
VIX - Volatility Index

The volatility index (VIX) is used as a proxy for market risk or the market's expectations of future volatility. The Norwegian Volatility Index (NOVIX) was recently created by Bugge et al. (2016), however, there is not enough data to cover this analysis. They compared NOVIX to the Chigaco Board Options Exchange Volatility Index (CBOE VIX) and the German Volatility Index (VDAX-NEW), where they found it to have the same properties as the two. Therefore, I find the CBOE VIX to be valid in this study. The index is calculated using midpoints of real-time S&P 500 Index option bid/ask price quotations (Cboe, 2019). Whaley (2000) and Giot (2005) find a negative relationship between the VIX and market returns, where the index is referred to as the 'fear index'. The same relation is expected for all industry indices in this paper. VIX is to my knowledge not used when analyzing macroeconomic variables and adds as a contribution to this area of study. The monthly averages of VIX are used.

4.2. Descriptive Statistics

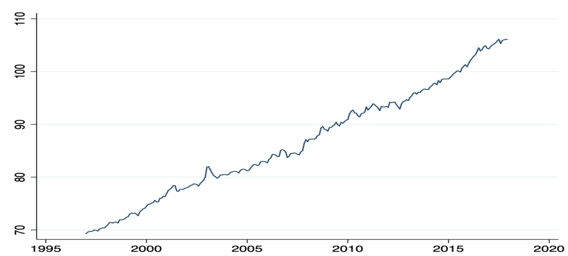
Appendix A.2 shows a line plot with market values for each industry portfolio. The largest portfolios are Energy, Finance, and Industrials, while the smallest are Utilities, Materials, and Health Care. Further, Figure 1 shows a line plot of the industry portfolio indices. The IT portfolio is the winner while the Materials portfolio has the lowest growth in the period. Figure 2 shows line plots for each macroeconomic variable in Levels in the relevant period. Appendices A.3 and A.4 show the histograms and normal distributions for the macroeconomic variables and the industry indices in First Difference. Appendix A.5 shows scatter plots of the macroeconomic variables against the Energy portfolio.

Figure 1: Time Series of the Industry Indices



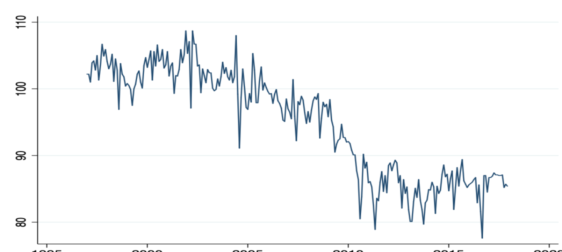
Line plot of the industry portfolio indices with start value = 100 in the period 1997M1-2017M12. The ten portfolios included are Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Health Care, Financials, IT, Telecom and Utilities.

Figure 2: Time Series Plots of Macroeconomic Variables

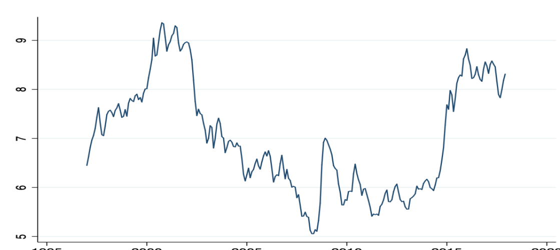


(a) CPI

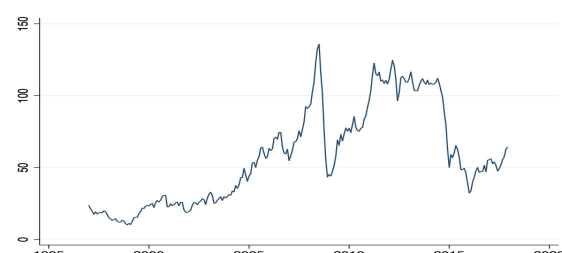
(b) TS



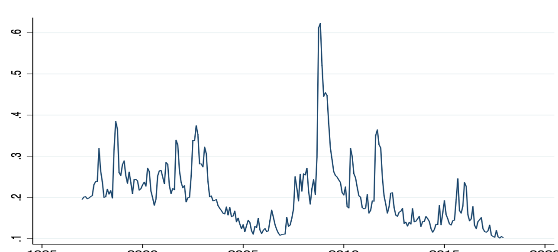
(c) IP



(d) ND



(e) OP



(f) VIX

Line plots of the macroeconomic variables in Levels in the period 1997M1-2017M12. From the top left we have CPI = consumer price index, TS = term spread, IP = industrial production, ND = USD/NOK exchange rate, OP = oil price, VIX = volatility index.

A summary of descriptive statistics of the industry indices in First Difference is presented in Table 2. In accordance with financial expectations the cyclical industries, Materials, and IT have the highest volatility because of elastic prices, while the less cyclical industries Utilities, Industrials, and Financials have the lowest volatility because of the necessities of these industries. All have kurtosis over three, with the Materials and Telecom industries having the highest, indicating more extreme values than expected in a normal distribution.

Table 2: Descriptive Statistics of Industry Indices in First Difference

Portfolio	Mean	Std. Dev.	Median	Min	Max	Skewness	Kurtosis
ΔEnergy (10)	0.4482	3.1841	0.4065	−14.3978	8.0156	−0.7423	5.1514
ΔMaterials (15)	0.2272	5.1772	0.3240	−25.7470	39.6135	1.2380	18.9786
ΔIndustrials (20)	0.5787	2.9677	0.9742	−12.9894	6.7056	−0.8617	5.1746
ΔConsDisc (25)	0.5599	4.6575	0.7715	−18.4892	21.9710	−0.2098	6.1209
ΔConsStapl (39)	0.5669	3.1392	0.7765	−15.4384	10.7005	−1.1490	7.6218
ΔHealth Care (35)	0.5021	3.1892	0.4062	−12.1065	15.2180	0.4458	7.1391
ΔFinancials (40)	0.5520	2.9909	0.8812	−12.2158	10.8358	−0.9661	6.4224
ΔIT (45)	0.7041	5.1431	0.8287	−19.7962	30.2643	0.0591	9.3669
ΔTelecom (50)	0.4989	4.5430	0.6117	−26.2634	12.3291	−1.4134	11.7040
ΔUtilities (55)	0.3437	2.9148	0.3292	−13.5469	13.9219	−0.3433	7.8393

Descriptive Statistics of industry indices in First Difference. The number of companies included in each portfolio is included in parenthesis. Mean, Std.Dev, Median, Min, and Max are reported as percentages. There are 239 observations of all industry returns. Sample period: 1997M1-2016M12.

Table 3 presents the descriptive statistics of the macroeconomic variables. Table A shows the variables in Levels and Table B show in First Difference. Table B shows that the Term Structure has the highest volatility, which can influence the accuracy of the result interpretations. In addition, CPI and OP grew slightly per month, the NOK weakened against the USD in the period, TS and VIX decreased somewhat, while IP had the least change per month in the period.

Table 3: Descriptive Statistics of Macroeconomic Variables

Panel A. Data in Levels						
	CPI	TS	IP	ND	OP	VIX
Mean	85.5533	0.3719	95.3638	6.9385	57.7318	20.9328
Std.Dev.	9.6464	1.2474	7.9743	1.1133	34.7293	8.0367
Minimum	68.8000	−2.9109	77.6000	5.0546	10.0204	10.7868
Maximum	104.9000	2.9195	108.7000	9.3613	135.7313	62.2535
Panel B. Data in First Difference						
Mean	0.0008	−0.0026	−0.0003	0.0005	0.0016	−0.0008
Std.Dev.	0.0019	0.3434	0.0132	0.0112	0.0386	0.0684
Minimum	−0.0056	−2.2140	−0.0426	−0.0261	−0.1343	−0.1647
Maximum	0.0102	1.6961	0.0497	0.0563	0.0864	0.3123

Descriptive statistics of the macroeconomic variables in Levels and First Difference. There are 240 observations of variables in Levels and 239 observations in First Difference. CPI = consumer price index, TS = term structure, IP = industrial production, ND = USD/NOK exchange rate, OP = oil price, VIX = volatility index. Sample period: 1997M1-2016M12.

Tables 4 and 5 display pairwise correlation coefficients for the macroeconomic variables in Levels and First Difference, respectively. After transforming the variables into First Difference, only ND are significantly correlated with OP and VIX at 1% level. The correlation between ND and OP is somewhat high, but not enough to be an issue in this analysis. Table A2 in the Appendix shows the correlations between the industry indices where all are significant at 1% level and positively correlated in First Difference.

Table 6 shows pairwise correlation coefficients for the industry indices and macroeconomic variables, where all are in First Difference. The exchange rate, oil price, and VIX have significant relations at 1% level. The exchange rate is negatively correlated with Energy, Industrials, and Financials, while the oil price has a positive relationship with the same industries. The VIX is negatively correlated with all industries.

Table 4: Correlation Matrix of Macroeconomic Variables in Levels

	CPI	TS	IP	ND	OP	VIX
CPI	1.0000					
TS	0.0621	1.0000				
IP	−0.8879*	−0.0704	1.0000			
ND	−0.3148*	−0.2348*	0.4071*	1.0000		
OP	0.6967*	0.0212	−0.7288*	−0.7799*	1.0000	
VIX	−0.2503*	−0.4587*	0.2654*	0.1531	−0.2439*	1.0000

* indicates the correlation is significant at 1% level. Pairwise correlation coefficients of macroeconomic variables in Levels in the period 1997M1-2016M12. CPI = consumer price index, TS = term structure, IP = industrial production, ND = USD/NOK exchange rate, OP = oil price, VIX = volatility index.

Table 5: Correlation Matrix of Macroeconomic Variables in First Difference

	ΔCPI	ΔTS	ΔIP	ΔND	ΔOP	ΔVIX
ΔCPI	1.0000					
ΔTS	−0.0411	1.0000				
ΔIP	0.0920	−0.0511	1.0000			
ΔND	0.0701	−0.0053	0.0437	1.0000		
ΔOP	−0.0414	0.0177	−0.0930	−0.4523*	1.0000	
ΔVIX	0.0060	0.1343	0.0148	0.1831*	−0.1655	1.0000

* indicates the correlation is significant at 1% level. Pairwise correlation coefficients of macroeconomic variables in First Difference in the period 1997M1-2016M12. CPI = consumer price index, TS = term structure, IP = industrial production, ND = USD/NOK exchange rate, OP = oil price, VIX = volatility index.

Table 6: Pairwise Correlations between the Industries and Macroeconomic Variables

	ΔCPI	ΔTS	ΔIP	ΔND	ΔOP	ΔVIX
ΔEnergy	−0.0131	−0.1194	0.0482	−0.1715*	0.3774*	−0.4231*
ΔMaterials	−0.0040	−0.0055	−0.0360	0.0306	0.0124	−0.2855*
ΔIndustrials	−0.0593	−0.1134	0.0270	−0.1746*	0.1693*	−0.5422*
ΔConsDisc	0.0003	0.0425	−0.0128	−0.0118	−0.0589	−0.4195*
ΔConsStapl	−0.0045	−0.0982	−0.0014	−0.1059	0.0602	−0.4823*
ΔHealthCare	−0.0655	0.0042	−0.0285	−0.0086	0.0703	−0.3792*
ΔFinancials	−0.0631	−0.1074	−0.0028	−0.2705*	0.1940*	−0.5516*
ΔIT	0.0001	−0.0697	0.1170	−0.0951	0.0387	−0.3728*
ΔTelecom	−0.0039	−0.1231	0.0836	−0.1562	0.0695	−0.3424*
ΔUtilities	−0.1125	−0.1207	−0.0321	−0.1296	0.0421	−0.3682*

* indicates variable is significant at 1% level. Pairwise correlation coefficients of the industry indices and macroeconomic variables in First Difference. CPI = consumer price index, TS = term structure, IP = industrial production, ND = USD/NOK exchange rate, OP = oil price, VIX = volatility index.

5. Empirical Tests and Results

The following section describes the tests conducted and comments on the results. The K-vector of variables, y_t, studied equals:

$$y_{t,II} = (II_t, CPI_t, TS_t, IP_t, ND_t, OP_t, VIX_t)$$

where II is the Industry Indices, one for each industry, giving ten models. By creating individual models for each industry, the relations of the macroeconomic variables is studied related to the specific industry. This also allows for forecast creations based on only the macroeconomic variables in combination with the industry index. As an example, the model for the Energy industry portfolio in combination with the macroeconomic variables, called the 'Energy Model', is:

$$y_{t,Energy} = (Energy_t, CPI_t, TS_t, IP_t, ND_t, OP_t, VIX_t)$$

To conduct the analysis seven steps are followed: (1) test for stationarity in each variable, (2) select number of lags for each model, (3) lag selections for each model, (4) test diagnostics for each model, (5) run VAR or VECM, (6) create 12-month forecasts based on the VAR or VECM, and (7) create IRF graphs based on the VAR or VECM. The results of each step are described and discussed next.

5.1. Stationarity

The ADF and PP tests are used to check for stationarity in all variables. Before the tests are run, the optimal number of lags for each variable is selected based on the AIC with a maximum of 14 lags as done by Mukherjee & Naka (1995). The line plots in Figure 1 and 2 show trends in the industry indices and CPI. Thus, these variables include both a trend, δt, and a constant, α, when testing for stationarity in Levels. The rest of the variables include only a constant. Table 7 lists the results for variables in Levels and First Difference. Only VIX is found to be stationary in Levels at 1% level by both tests. To create stationary variables, the first difference of log-transformed variables are tested, where all are found to be stationary at 1% level by both tests.

Table 7: Unit Root Tests

	Levels			First Difference		
	# lags	ADF	PP	# lags	ADF	PP
Energy	2	-3.251^{*}	-2.868	1	-9.730^{***}	-13.445^{***}
Materials	5	-1.267	-1.043	1	-11.433^{***}	-17.142^{***}
Industrials	2	-1.790	-1.686	1	-9.805^{***}	-12.844^{***}
ConsDisc	13	-3.840^{**}	-1.631	1	-11.185^{***}	-14.030^{***}
ConsStapl	3	2.343	2.651	0	-14.541^{***}	-14.541^{***}
Health Care	5	1.355	2.413	4	-5.973^{***}	-14.145^{***}
Financials	2	-1.636	-1.530	1	-9.466^{***}	-13.267^{***}
IT	14	-0.789	-0.854	0	-14.690^{***}	-14.690^{***}
Telecom	1	-2.053	-2.017	3	-6.548^{***}	-13.994^{***}
Utilities	2	-1.026	-0.901	2	-8.614^{***}	-13.410^{***}
CPI	14	-1.439	-2.458	13	-4.085^{***}	-15.086^{***}
TS	6	-3.801^{***}	-3.071^{**}	5	-8.093^{***}	-17.924^{***}
IP	14	-0.455	-2.121	13	-5.328^{***}	-33.887^{***}
ND	2	-1.273	-1.191	1	-9.393^{***}	-10.582^{***}
OP	2	-2.045	-1.656	1	-9.273^{***}	-11.644^{***}
VIX	3	-3.532^{***}	-4.008^{***}	7	-6.993^{***}	-15.462^{***}
Critical Values with Constant						
	1 %	5 %	10 %			
	-3.46	-2.88	-2.57			
Critical Values with Constant and Trend						
	1 %	5 %	10 %			
	-3.99	-3.43	-3.13			

Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests for stationarity for all variables in Levels and First Difference. The number of lags is determined by the AIC with maximum lags at 14. All tests include a constant, while a trend is added to the Industry Indices and CPI in Levels. The Test Statistics are reported in the table. CPI = consumer price index, TS = term structure, IP = industrial production, ND = USD/NOK exchange rate, OP = oil price, VIX = volatility index. Sample period: 1997M1-2016M12.

5.2. Cointegration

Each model in Levels is tested for cointegration through the Johansen test. Table 8 shows the results for the Energy Model, including the Energy index in combination with the macroeconomic variables as an example. The null hypothesis states that the number of cointegrations is maximum r. The first null hypothesis for $r = 0$ is tested and accepted. Thus, the test concludes that there are no cointegrated equations in the model. Appendix B.6 show the results of the other models where $r = 0$ is rejected, and either $r = 1$, $r = 2$ or $r = 3$ are accepted. Thus, long-run relationships exist between the variables in each model, except in the Energy Model. The VAR approach will be used to analyze the Energy model, while the VECM approach will be used for the other nine models.

Table 8: Johansen Cointegration Test for the Energy VECM

r	Eigenvalue	Trace Statistic	5% Critical Value
0		121.12 *	124.24
1	0.1485	82.86	94.15
2	0.1304	49.62	68.52
3	0.0867	28.03	47.21
4	0.0509	15.61	29.68
5	0.0458	4.46	15.41
6	0.0114	1.74	5.76
7	0.0073		

Johansen test for cointegration on the Energy Model including the Energy index in combination with the macroeconomic variables. All variables are in Levels in the period 1997M1-2016M12. The Trace Statistics and their corresponding Critical Values at 5% are reported.

5.3. Lag Selection

Table 9 shows the lag selection for the Energy Model as an example, where the values are log-transformed. Maximum 12 lags are tested as Kwon & Shin (1999) recognize up to 12 lags to be sufficient with monthly data. The likelihood ratio (LR) statistics, Akaike's Information Criterion (AIC) and Hannan-Quinn Information Criterion (HQIC) are compared. All ten variables have the same results, with HQIC selecting one lag, AIC selecting two lags and LR selecting 12 lags. Liew (2004) finds HQIC to best find optimal lag length when the sample size is greater than 120. However, when using one lag, the residuals are autocorrelated in all ten models. Gjerde & Saettem (1999) use AIC even though their sample size is greater than 120. To make sure the correct number of lags is chosen, each model is run with 1-12 lags, where the AIC for each analysis is compared. If too few lags are included, valuable information might be omitted, while if too many lags are included, the parameter estimated might become uncertain (Bjørnland & Thorsrud, 2014). For all models one lag has the lowest AIC, however, the residuals are autocorrelated. Two lags prove to have the second lowest AIC and no autocorrelated residuals. Thus, two lags are used for each model, which corresponds with the number of lags chosen by AIC. Note that the number of lags in a VECM is one less than in the underlying VAR. Thus when running the VECMs, three lags are specified when running a two-lag model.

Table 9: Lag Selection for the Energy Model

Lag	LR	AIC		HQIC	
0		−14.72		−14.68	
1	3996.10	−31.82		−31.48	*
2	147.64	−32.04	*	−31.40	
3	77.26	−31.95		−31.01	
4	70.89	−31.83		−30.60	
5	54.82	−31.64		−30.11	
6	64.95	−31.50		−29.67	
7	73.36	−31.39		−29.26	
8	53.45	−31.19		−28.77	
9	98.04	−31.19		−28.47	
10	63.49	−31.04		−28.02	
11	69.45	−30.92		−27.60	
12	90.56*	−30.88		−27.27	

Lag selection criteria for the Energy Model, meaning the Energy industry in combination with the macroeconomic variables. Reported are LR-statistics, AIC, and HQIC. The log transformed variables are used in the period 1997M1-2016M12. Maximum 12 lags are tested as monthly observations are used (Kwon & Shin, 1999).

5.4. Diagnostics

Finally, diagnostics are run for each model to evaluate the models. All models with two lags have no autocorrelated residuals. Appendix B.7 shows the Lagrange-Multiplier Tests for all ten models, while Table 10a shows the test for the Energy Model as an example. The null hypothesis states that there is no autocorrelation at the lag order. The test rejects the null hypothesis at 5% level for both lags. This is also the case for the other nine models.

Figure 10b shows the eigenvalue stability condition for the Energy Model as an example. All the eigenvalues lie inside the unit circle and the VAR satisfies the stability condition. The VEC models are stable if the K-r eigenvalues are less than one. The nine VECMs have seven variables and one cointegrated equation giving K-r = 7 - 1 = 6 unit moduli in the companion matrix. As shown in Appendix B.8 the remaining eigenvalues are less than one, and the models are stable converging toward long-term equilibrium.

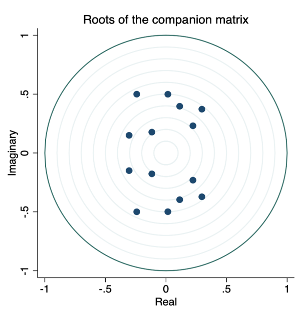
The main problem is the normally distributed disturbances where only the individual equation for ND is normally distributed in all ten models. Appendix B.9 shows the Jarque-Bera tests for all ten models, while Table 10c shows the test for the Energy Model as an example. The individual equations for oil price and VIX have normally distributed disturbances in the Telecom and Industrial Models, respectively. This is not necessarily a big weakness as the number of observations is large, and regression theory states that the disturbances follow the normal distribution when the sample size is sufficient.

Table 10: Diagnostics Tests for the Energy Model

(a) Lagrange-Multiplier Test

Lag	chi2	df	Prob > chi2
1	52.169	49	0.352
2	59.166	49	0.152

(b) Eigenvalue stability condition



(c) Jarque-Bera Test

Equation	chi2	df	Prob > chi2
Δ Energy	26.414	2	0.000
Δ CPI	68.385	2	0.000
Δ TS	663.543	2	0.000
Δ IP	31.894	2	0.000
Δ ND	0.161	2	0.923
Δ OP	13.497	2	0.001
Δ VIX	30.644	2	0.000
ALL	834.538	14	0.000

Diagnostics tests for the Energy Model, meaning a VAR of the Energy industry in combination with the macroeconomic variables, with two lags. Sample period: 1997M1-2016M12.
(a) Lagrange-Multiplier Test with H_0 = no autocorrelation at lag order.
(b) Eigenvalue stability condition: All the eigenvalues lie inside the unit circle. VAR satisfies the stability condition.
(c) Jarque-Bera Test with H_0 = the disturbances in the VAR are normally distributed.

5.5. VAR and VECM Results

This section describes the results of each model and discusses the short- and long-run relationships. Ten models are analyzed based on monthly observations in the period 1997M1-2016M12. Each model is specified based on the results of lag selections and the cointegration tests. Table 11 summarize these results and specifies the approach used for each model as well as the input variables used. Note that a VAR is run for the Energy Model where only short-run relations can be interpreted. For the other nine models Rank=1 for simplicity. This paper intends to explore the relationships between industry portfolios and macroeconomic variables and is the first of its kind. Thus, further analysis of this topic should use ranks found by the Johansen test for cointegration. The discussion will focus on the specific relations between the industries and the macroeconomic variables, as well as if the industries behave differently from each other. If the industries behave differently, there exist diversification opportunities for portfolio managers.

Table 11: Model Fit

Model	Lag selection	Rank	Approach	Input Variables
$y_{t,Energy}$	2	0	VAR	First Difference
$y_{t,Materials}$	2	1	VECM	Log-Transformed
$y_{t,Industrials}$	2	1	”	”
$y_{t,ConsDisc}$	2	1	”	”
$y_{t,ConsStapl}$	2	3	”	”
$y_{t,HealthCare}$	2	2	”	”
$y_{t,Financials}$	2	2	”	”
$y_{t,IT}$	2	1	”	”
$y_{t,Telecom}$	2	1	”	”
$y_{t,Utilities}$	2	1	”	”

Number of lags reported are based on Akaike’s Information Criterion where the log-transformed variables are used. Ranks reported are based on Johansen test for cointegration on variables in Levels. The Models are as described earlier where for example $y_{t,Energy} = (Energy_t, CPI_t, TS_t, IP_t, ND_t, OP_t, VIX_t)$. CPI = consumer price index, TS = term structure, IP = industrial production, ND = USD/NOK exchange rate, OP = oil price, VIX = volatility index. Sample period: 1997M1-2016M12. The model approach is determined by number of cointegrated equations, where the Energy Model is the only with zero cointegrated equations. Log-transformed variables are input in the VECMs as the model turns these into First Differences. ” suggests VECM approach and Log-Transformed variables as input.

5.5.1. Short-Run Relationships

Table 12 shows the short-run relations for all industries according to their respective models. Only variables significant at 5% level or lower are reported. The Health Care, Financials, and Telecom portfolios are not related to own or other lagged values in the short-run. All the other industries, except Utilities, have a relation to the lagged values of TS. The relations are positive, which corresponds to the results of Gjerde & Saettem (1999). They find the Norwegian market to respond spontaneously negative to changes in NIBOR, and when NIBOR decreases, TS increases. Thus, all the significant relationships with TS follows the Norwegian market's relationship with TS.

The second lag of OP has a relation to the Industrials and Utilities portfolios. The positive relation is as expected, while the Industrials industry does not benefit from an increase in OP in the short-run. This could be because a major expense in the industry is oil. In addition, I would expect OP to have a short-run relation to Energy, but this is not found. The first and second lags of IP influence the Materials portfolio negatively in the short run. This is opposite to the expectations, indicating that an increase in IP is not beneficial for the Materials industry in the short-run. The reason might be that an increase in IP influence future cash flows in the Materials industry negatively. Overall, the industries have different short-run relations to the macroeconomic variables, giving portfolio managers diversification opportunities.

Table 12: Short-Run Relations

$\Delta Energy_t =$		$+0.0203\,\Delta TS^{***}_{t-1}$		
$\Delta Materials_t =$		$+0.0519\,\Delta TS^{***}_{t-2}$	$-0.5813\,\Delta IP^{**}_{t-1}$	$-0.6271\,\Delta IP^{**}_{t-2}$
$\Delta Industrials_t =$	$+0.0060^{**}$	$+0.1763\,\Delta Industrials^{**}_{t-1}$	$+0.0135\,\Delta TS^{**}_{t-1}$	$-0.1168\,\Delta OP^{**}_{t-2}$
$\Delta ConsDisc_t =$		$+.0197\,\Delta TS^{**}_{t-2}$		
$\Delta ConsStapl_t =$	$+0.0075^{***}$	$+0.0160\,\Delta TS^{**}_{t-1}$		
$\Delta HealthCare_t =$	$+0.0070^{***}$			
$\Delta Financials_t =$	$+0.0068^{**}$			
$\Delta IT_t =$	$+0.0111^{***}$	$-3.5951\,\Delta CPI^{**}_{t-2}$	$+0.0270\,\Delta TS^{**}_{t-1}$	
$\Delta Telecom_t =$	$+0.0078^{**}$			
$\Delta Utilities_t =$	$+0.0052^{**}$	$-0.1897\,\Delta Utilities^{**}_{t-2}$	$+0.1344\,\Delta OP^{**}_{t-2}$	

,* show significance level at 5% and 1% level respectively. Short-run relations for each model in the period 1997M1-2016M12. Δ indicates log return. CPI = consumer price index, TS = term structure, IP = industrial production, ND = USD/NOK exchange rate, OP = oil price, VIX = volatility index.

5.5.2. Long-Run Relationships

To interpret the adjustment parameters, α, in the VEC models the coefficient of the lagged error correction term to the industry portfolio needs to be negative and significant. Note that no long-run relationships exist with the Energy Model as no cointegrated relations are found. Table 13 displays the coefficients to the error correction terms for each model. The second column (ΔII) shows the coefficients to the error correction term for each industry index and is the most interesting for this analysis. We see that three of the industries do not have negative and significant parameters. This indicates that if in disequilibrium, the models would diverge from equilibrium. Thus, there might be some specification problems in these models. For the remaining models, however, an adjustment parameter can be interpreted. If in disequilibrium the Materials, Health Care, ConsDisc, Telecom, IT and Utilities models are each month corrected by 5.81%, 4.72%, 4.47%, 3.66%, 0.68%, and 0.04% respectively.

Table 13: Coefficients to Error Correction Term

Model	Δ II	Δ CPI	Δ TS	Δ IP	Δ ND	Δ OP	Δ VIX
$y_{t,Material}$	-0.0581^{***}	0.0008	-0.5299^{***}	0.0137^{***}	-0.0004	-0.0103	-0.0343
$y_{t,Industrials}$	-0.0001	0.0002	-0.0780^{***}	0.0006	-0.0001	-0.0013	-0.0080^{**}
$y_{t,ConsDisc}$	-0.0447^{**}	0.0021^{**}	-0.6112^{***}	-0.0013	0.0022	-0.0017	-0.0518^{*}
$y_{t,ConsStapl}$	-0.0063	0.0005^{*}	-0.2026^{***}	0.0008	-0.0003	-0.0012	-0.0259^{***}
$y_{t,HealthCare}$	-0.0472^{***}	0.0019^{**}	-0.4848^{***}	0.0030	-0.0012	-0.0047	-0.0804^{**}
$y_{t,Financials}$	-0.0053	0.0008^{*}	-0.3836^{***}	0.0034	-0.0001	-0.0067	-0.0205
$y_{t,IT}$	-0.0068^{*}	0.0002	-0.1014^{***}	-0.0001	0.0002	-0.0005	-0.0113^{**}
$y_{t,Telecom}$	-0.0366^{***}	0.0007	-0.2688^{***}	-0.0042	0.0011	-0.0002	-0.0313^{**}
$y_{t,Utilities}$	0.0004^{**}	0.0000	0.0069^{***}	-0.0001	0.0000	0.0002	0.0013^{***}

*, ** and *** show significance level at 10%, 5% and 1% level respectively. The coefficient of each error correction term are reported based on their respective VECM. CPI = consumer price index, TS = term structure, IP = industrial production, ND = USD/NOK exchange rate, OP = oil price, VIX = volatility index. Sample period: 1997M1- 2016M12.

The long-run relationships are interpreted from the cointegrated vector, which is retrieved from Johansen normalization. We get the long-run relations by normalizing each portfolio index to 1. For example, the cointegrated vector for the Materials VECM is:

$$\beta_1' = (+1.00, -6.43, +0.31, -9.50, +0.89, +0.65, +1.47)$$

where the values represent coefficients for the Materials index normalized to one, CPI, TS, IP, ND, OP, and VIX respectively. These represent long-run elasticity measures due to the logarithmic transformations. As done by Mukherjee & Naka (1995), the signs of the coefficients are changed when interpreting them as displayed in Table 14.

Table 14: Long-Run Relations

$Materials_t =$	$+6.43CPI_t^{***}$	$-0.31TS_t^{***}$	$+9.50IP_t^{***}$	$-0.89ND_t$	$-0.65OP_t^{**}$	$-1.47VIX_t^{***}$
$Industrials_t =$	$+14.08CPI_t$	$-2.98TS_t^{***}$	$+19.58IP_t$	$-18.61ND_t^{**}$	$-3.36OP_t$	$-4.99VIX_t^{***}$
$ConsDisc_t =$	$+6.07CPI_t^{***}$	$-0.28TS_t^{***}$	$-1.26IP_t$	$-0.88ND_t$	$-0.57OP_t^{**}$	$-1.32VIX_t^{***}$
$ConsStapl_t =$	$+5.48CPI_t$	$-0.99TS_t^{***}$	$+3.92IP_t$	$-3.15ND_t$	$-0.47OP_t$	$-2.44VIX_t^{***}$
$HealthCare_t =$	$+4.90CPI_t^{***}$	$-0.16TS_t^{***}$	$+1.33IP_t$	$-0.42ND_t$	$-0.28OP_t$	$-1.38VIX_t^{***}$
$Financials_t =$	$+8.46CPI_t^{***}$	$-0.66TS_t^{***}$	$+4.64IP_t$	$-3.66ND_t^{**}$	$-0.60OP_t$	$-0.96VIX_t^{**}$
$IT_t =$	$-7.72CPI_t$	$-2.21TS_t^{***}$	$-3.21IP_t$	$-6.05ND_t$	$-0.40OP_t$	$-3.95VIX_t^{***}$
$Telecom_t =$	$-2.39CPI_t$	$-0.53TS_t^{***}$	$-7.59IP_t^{***}$	$-2.94ND_t^{**}$	$-0.57OP_t$	$-1.44VIX_t^{***}$
$Utilities_t =$	$-168.67CPI_t$	$+16.46TS_t^{***}$	$-247.12IP_t^{**}$	$+116.46ND_t^{**}$	$+35.46OP_t^{**}$	$+70.35VIX_t^{***}$

** and *** show significance level at 5% and 1% level respectively. Long-run relations for the VEC models with negative and significant error correction terms in the period 1997M1-2016M12. As a VAR is run for the Energy model, no long-run relations exist. CPI = consumer price index, TS = term structure, IP = industrial production, ND = USD/NOK exchange rate, OP = oil price, VIX = volatility index.

The significant long-run findings include negative relations with TS and VIX for all portfolios, except Utilities. CPI has only significant positive relations, ND and OP have mainly negative relations, while IP varies the most. The Utilities industry stands out with opposite relationships to all variables, except CPI and IP. This might be due to its non-cyclical characteristics where its goods and services are needed in the economy no matter what the economic situation is. The relations indicate that if interest rates increase, the NOK weakens, the industrial production decrease, the oil price increase or the market risk increase, the Utilities portfolio would still increase. Lastly, the Utilities and Materials have different relations to both IP and OP in the long-run. This could be explained by their cyclical and non-cyclical nature. Thus, there are differences between the industries regarding the long-run relations with the macroeconomic variables, except the CPI. The long-run relations to each macroeconomic variable are discussed next and compared to existing literature.

Consumer Price Index

The findings suggest a significant positive long-run relationship between CPI and the Materials, ConsDisc, Health Care, and Financials portfolios. This is not as expected, but is supported by the findings of Hamao (1988). The significant findings include both cyclical and non-cyclical industries, thus showing no differences between industries regarding long-run relationships with CPI. The positive relations could indicate strong cash flows within these industries, which rise with inflation. Gjerde & Saettem (1999) find no relation between the market and inflation, which I find for the other five industries.

Term Structure

The findings suggest a significant negative long-run relationship between TS and all the portfolios, except Utilities. Thus, the non-cyclical Utilities industry differs from the others. Finding TS to be significant with returns are consistent with the research of Chen et al. (1986), Hamao (1988) and Chen (1991). The negative relations are supported by the findings of Eliassen & Vik (2010) who find a negative relation between the term structure and the Norwegian stock market, indicating that all the industries except Utilities have a similar relationship with TS as the stock market.

Industrial Production

IP has a positive long-run relation to the Materials portfolio, which is supported by my expectations and the U.S. and Japanese findings of Chen et al. (1986), Hamao (1988) and Mukherjee & Naka (1995). The Telecom and Utilities portfolios, however, have negative relations to IP. Again, the Utilities industry moves opposite as expected. Thus, the long-run relations to IP are different between these industries, where the cyclical Materials industry follows the expectation and findings of previous studies.

Exchange Rate

ND has significant and negative relations to the Industrials, Financials, and Telecom portfolio, which is not as expected and opposite as the findings of Mukherjee & Naka (1995). However, it is supported by the results of Rongved & Solberg (2018), who find the Norwegian stock market to have a negative relation with the USD/NOK exchange rate. Thus, these three industries follow the Norwegian market related to the exchange rate and behave similarly. A reason for this could be that these industries and the market, rely on imports where a weak NOK leads to higher costs as foreign goods become more expensive. The Utilities industry, on the other hand, has a positive relationship with ND. Thus, when the NOK weakens against the USD, the Utilities industry reacts positively. Again, this could be because of its non-cyclical behavior, or because the industry relies on exports rather than imports.

Oil Price

OP has a significant negative long-run relation with Materials and ConsDisc, and a positive relation with Utilities. The cyclical and non-cyclical industries behave differently. The negative relationships could indicate that a major expense of the industries is oil, where a decrease would benefit them. The Utilities portfolio, however, behaves as expected where it benefits from an increase in the oil prices, which could be because it includes electric and gas utilities (see Appendix A1).

Volatility Index

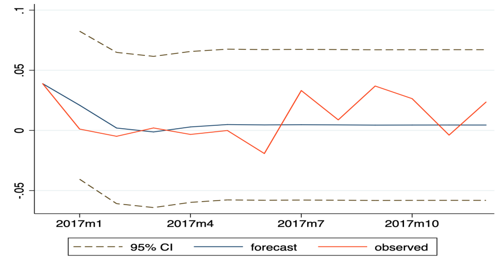
VIX has a significant negative relation with all industry portfolios, except Utilities. As expected, an increase in market risk influence the industry returns negatively and is consistent with the findings of Whaley (2000) and Giot (2005). The surprising result is the Utilities industry, which has a positive relation to market risk. As mentioned, this is consistent with the Utilities industry being non-cyclical.

5.6. Forecasts

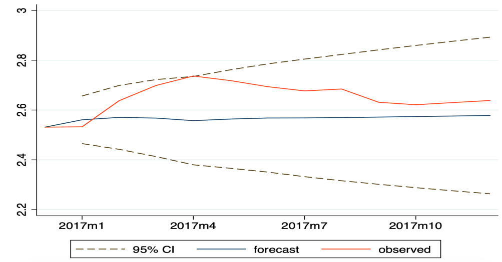
Based on the VAR and VEC models, 12-month out-of-sample forecasts for 2017 are compared to actual observed values. This section comments on the forecast ability for each model, where the focus in only on the forecasts for each industry index as this is the main focus for this thesis.

Figure 3 graphs the predictions of each portfolio based on their respective models. The Energy portfolio shows the log returns while the others show log-transformed values. Industrials and IT have the most accurate forecasts. The Energy forecast is accurate the first five months with log returns around zero but miss the next months' variations. The forecast for the Materials portfolio has forecast below observed values in almost the whole period and miss the increase between February and August. The Telecom portfolio forecast end-value misses the actual end-value by the most, where the forecasts are below observed values for all but the first month. Overall, all the VECM forecasts have a slight upward slope, indicating a positive trend, however, they do not capture monthly deviations. For portfolio managers, the forecasts give limited information on possible diversification strategies.

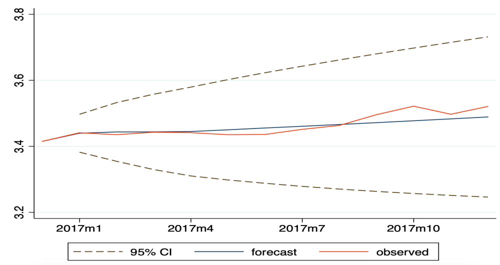
Figure 3: 12-Month Forecasts



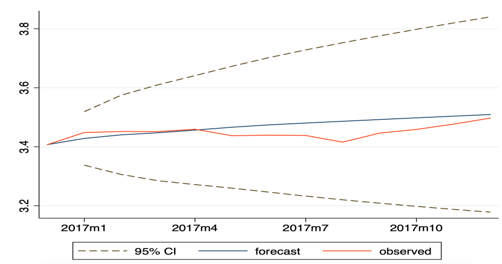
(a) Energy



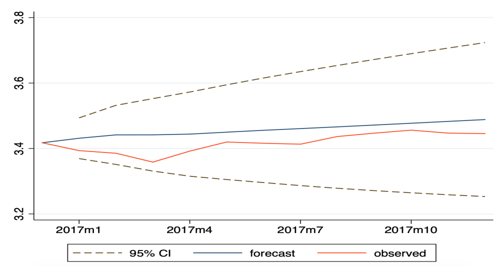
(b) Materials



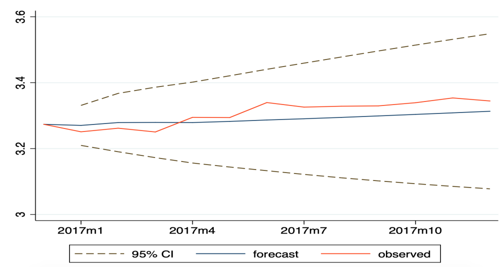
(c) Industrials



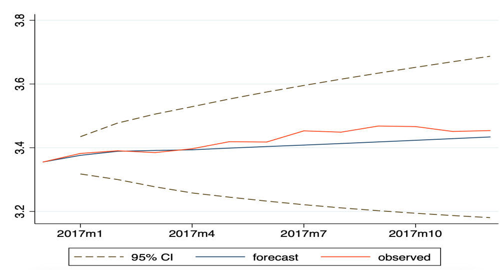
(d) Consumer Discretionary



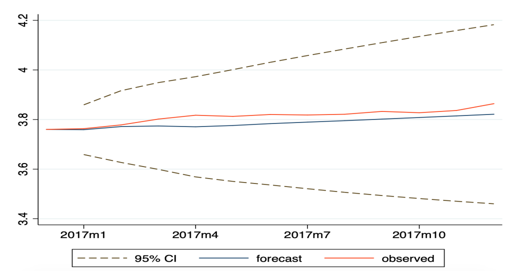
(e) Consumer Staples



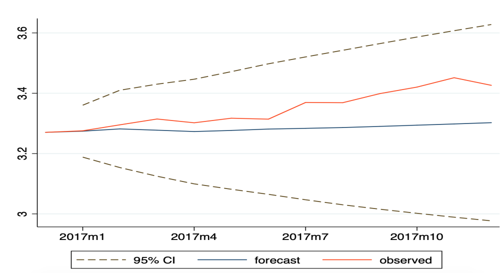
(f) Health Care



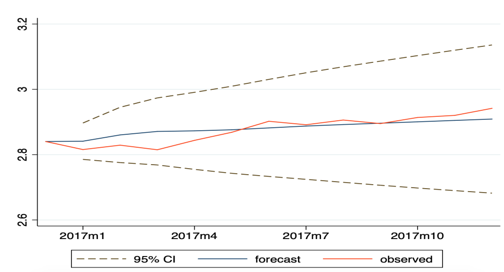
(g) Financials



(h) IT



(i) Telecom



(j) Utilities

12-month forecasts for each industry portfolio based on their respective model. Actual 2017 observations are compared to the forecasts. The 95% confidence intervals are included.

5.7. Impulse Response Functions

Figure 4 show the 12-step IRF graphs for each portfolio based on their respective models. Only responses from the industry portfolio from one-standard-deviation shocks in the macroeconomic variables are interpreted as this is the main focus of this thesis. Overall, the industries respond similarly to shocks in TS and VIX but respond differently to shocks in the other macroeconomic variables. This offers diversification opportunities for portfolio managers. Most surprising is the response from the Utilities industry, where the significant long-run relations found between the industry and TS, IP, ND, and VIX are not reflected in its IRF graphs. Instead, the Utilities industry has similar responses as the others. The rest of this section discusses the results of shocks in each macroeconomic variable.

Consumer Price Index

Unexpected shocks in CPI has a permanent effect on all portfolios except for Energy and Health Care. All except Materials and ConsDisc have negative responses to shocks in CPI. The permanent positive response from Materials and ConsDisc corresponds with the finding of a positive long-run relationship with CPI. The negative responses are supported by financial theory and the findings of Chen et al. (1986) and Mukherjee & Naka (1995) for macroeconomic variables and the U.S. and Japanese stock markets. Thus, the industries respond differently to shocks in CPI.

Term Structure

The portfolios react similarly to a shock in TS, where the initial response is positive before returning to zero, as for Energy and Industry, or becoming negative, as for the rest. The responses align with previous results of both the short- and long-run relationships, except for the Utilities industry. The initial responses support the initial negative response of the Norwegian market to shocks in NIBOR found by Gjerde & Saettem (1999). In addition, the long-run results support the findings of Eliassen & Vik (2010). Thus, the industries respond similarly to changes in TS as the market.

Industrial Production

The Materials, Utilities, and Telecom portfolios have the biggest responses to IP, where the two former respond positively while the latter respond negative, all with permanent effects. The responses of the Materials and Telecom portfolios fit with the long-run relations found earlier. Again, the

Utilities industry shows the opposite response compared to its long-run relation to IP found in the VECM. Gjerde & Saettem (1999) find an initial positive response of the stock market to shocks in IP, indicating that the Materials industry responds similarly as the Norwegian market. I expected the Energy industry to follow the market closest as 35% of the OSEAX consist of companies from this industry. However, it has a small initial negative response, before turning positive and lastly reverting to zero. Overall, the responses to shocks in IP differ between the industries.

Exchange Rate

Shocks in ND have permanent effects on ConsDisc, Telecom, and ConsStapl. The two former have negative responses, while the latter has a positive response. The permanent negative effect of Telecom corresponds with the long-run, negative relation found earlier. The Materials, Industrials, Financials, and IT have similar responses to shocks in ND, where there is an initial negative response before reverting to zero. Again, the industries have different responses to shocks in the macroeconomic variable.

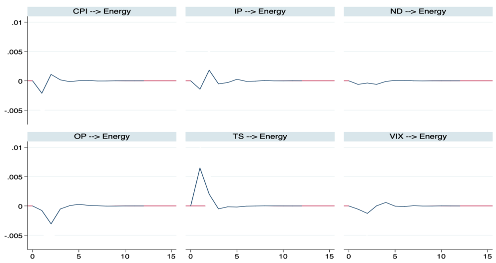
Oil Price

The Materials, Industrials, ConsDisc, and ConsStapl have an initial positive response to unexpected changes in OP, while Energy, Health Care, Financials, IT, Telecom, and Utilities have an initial negative response. Gjerde & Saettem (1999) find an initial positive response of the stock market to shocks in OP, then changing to negative and again positive before returning to zero. None of the industries follow these findings. Overall, the industries respond differently to shocks in OP.

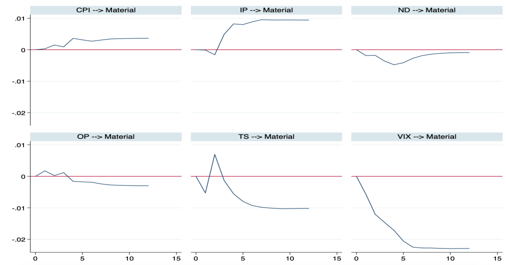
Volatility Index

All portfolios respond negatively to a shock in VIX except for the Industrials portfolio, where an unexpected shock in VIX results first as a positive response, before turning slightly negative. The negative response fits with the long-run relations commented earlier, and the findings of Giot (2005). All shocks have a permanent effect on all portfolios, except for the Energy portfolio.

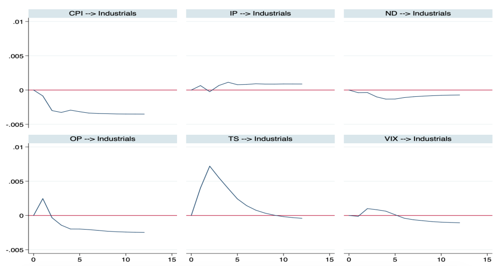
Figure 4: IRF Graphs



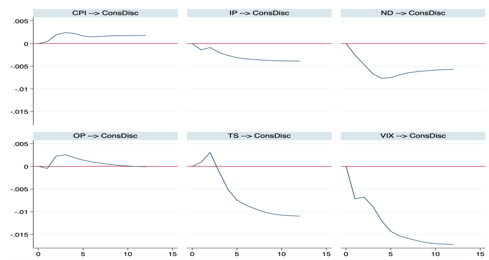
(a) Energy



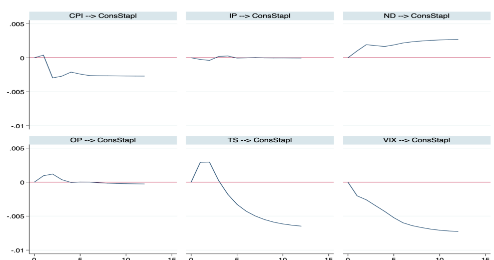
(b) Materials



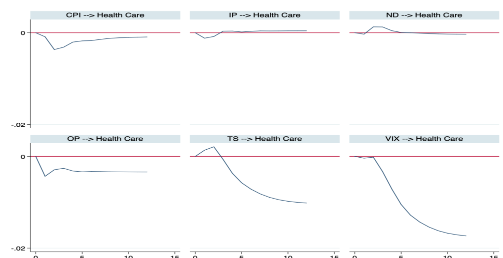
(c) Industrials



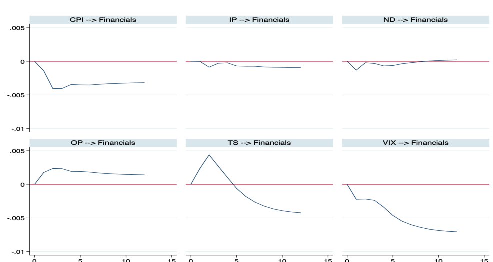
(d) Consumer Discretionary



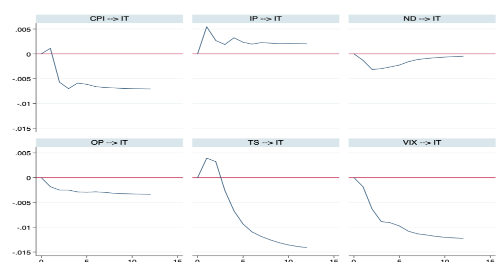
(e) Consumer Staples



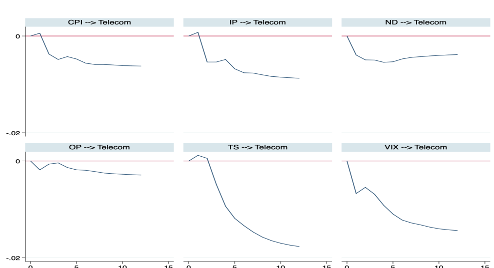
(f) Health Care



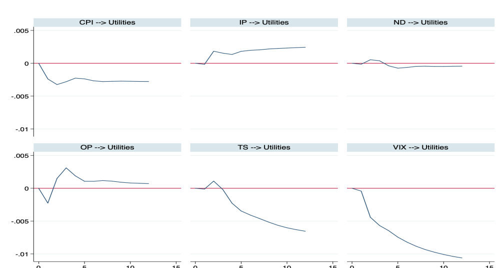
(g) Financials



(h) IT



(i) Telecom



(j) Utilities

IRF graphs for impulses in the macroeconomic variables on the industry portfolios, based on their respective models. The response is shown in 12 steps after the shock.

6. Discussion and Implications

This section discusses the theoretical and practical implications of this thesis, limitations of it, possible future research, and ends with a conclusion.

6.1. Theoretical Implications

The motivation for this thesis is to contribute to the literature on the relationship between macroeconomic variables and industry portfolios. Four research questions are created to fulfill this goal. These are answered in section 6.1.1, while section 6.1.2 compares the results with existing literature, before the overall theoretical implications of this thesis are discussed in section 6.1.3.

6.1.1. Answering the Research Questions

The first research question is as follows: *Are there short- and long-run relations between macroeconomic variables and Norwegian industries?* The Energy Model is the only industry that does not have long-run relations with the macroeconomic variables. For the other nine industries, cointegrated equations are found and both short- and long-run relations exist. This thesis presents and discusses all relations significant at 5% level based on the VAR approach for the Energy Model and the VECM approach for the others.

The second research question states: *Do Norwegian industries have different relationships with the macroeconomic variables?* The ten models show differences between their industries in the significant short- and long-run relations with the macroeconomic variables. This opens the possibility of diversifying between industries. The overall relationships to each are discussed in section 6.1.2.

The third research question states: *Can macroeconomic variables forecast future values of industry indices in Norway?* The forecasts for each industry portfolio are found to be decent, however, monthly deviations are not captured. The Industrials and IT indices have the most accurate forecasts, while forecasts for the Telecom and Materials indices are least accurate. Thus, the forecasts have limited power to predict future values of the industry indices.

The fourth and final research question is: *How do Norwegian industries respond to shocks in macroeconomic variables?* Overall, the industries respond differently to shocks in the macroeconomic variables. The majority of portfolios respond with a permanent negative effect to unexpected shocks in TS and VIX. Shocks to IP and ND get the least response from the portfolios. The relations and responses to each macroeconomic variable are discussed in greater detail next and compared with previous literature. This gives a greater answer to research question two and four by going through the actual short- and long-run relation to each variable, as well as the responses to unexpected shocks in them.

6.1.2. Comparisons with Existing Literature

The significant long-run relationships between CPI and the Materials, ConsDisc, Health Care, and Financials industries follow the findings of Hamao (1988), where a positive relation is found. However, the results of the IRF graphs show negative responses to shocks in CPI for all except Materials and ConsDisc. The negative response is as expected and supported by findings of Chen et al. (1986) and Mukherjee & Naka (1995), where a negative response to shocks in CPI is found.

Six industries have significant, positive short-run relations to TS. However, eight significant long-run relationships are negative. These relations are reflected in the IRF graphs, where the initial response to the majority of industries is positive before returning to zero or becoming negative. This supports the initial, negative response of the Norwegian market to shocks in NIBOR found by Gjerde & Saettem (1999). In addition, the long-run results support the findings of the Norwegian study by Eliassen & Vik (2010). Thus, the industries respond similarly to changes in TS as the market.

IP has only one significant, negative short-run relation to the Materials industry. The long-run relationships are with the Materials (+), Telecom (-) and Utilities (-) industries. The IRF graph between IP and the Materials industry fits with both the short- and long-run relations. The positive relation corresponds with the expectations and the findings of Chen et al. (1986), Hamao (1988), and Mukherjee & Naka (1995). The industries without significant relationships to IP have minimal responses to shocks in the variable.

The majority of the results for ND is not as expected. I find a negative, long-run relationship between ND and the Industrials, Financials, and Telecom industries. Thus, when the NOK weakens against the USD, these industries are affected negatively. The results are similar to that of the Norwegian study by Rongved & Solberg (2018) but opposite as to the findings of Mukherjee &

Naka (1995). Utilities is the only industry with a positive long-run relation, which might be due to non-cyclical behavior. In addition, all the industries, except ConsStapl and Health Care, respond negatively to shocks in ND.

The second lag of OP has a significant, negative short-run relation to the Industrials industry and positive relation to the Utilities industry. In addition, OP has a significant, negative long-run relation to the Materials and ConsDisc industries, and a positive relation to the Utilities industry. The industries respond differently to shocks in OP, where the Materials, Industrials, ConsDisc, and ConsStapl have an initial positive response, while Energy, Health Care, Financials, IT, Telecom, and Utilities have an initial negative response. Thus, the industries respond very differently to changes in OP, with few following the Norwegian market as Gjerde & Saettem (1999) find it to respond positively to oil price changes.

The VIX is found to have negative long-run relations to all industries, except the Utilities industry. The IRF graphs show a negative response in all industries, except Industrials. As expected, when the 'fear index' increases, most of the indices decrease. This is also supported by Whaley (2000) and Giot (2005).

6.1.3. Overall Theoretical Implications

Answering the research questions together gives the conclusion that the macroeconomic variables have different relations to Norwegian industries. Both the VAR and VECM approaches are used to explain these relationships, where forecasts with limited accuracy and IRF graphs are interpreted. Overall, this thesis contributes to the existing literature by supplementing previous research on macroeconomic factors and markets as a whole, especially Norwegian studies. In addition, by looking at all industries in the economy, this thesis opens for looking at diversification opportunities.

6.2. Practical Implications

How diversification strategies are formed depends on the portfolio manager. However, these results could give insight into strategies fitting their objectives. The industries show different short- and long-run relations as well as responses to shocks in the macroeconomic variables, indicating that there exist diversification opportunities. The forecasts miss monthly deviations and provide little information on possible diversification strategies.

The most interesting results regarding the industries are for the Utilities portfolio. The Utilities industry has opposite long-run relations to most of the macroeconomic variables compared to the other industries. This might be due to its non-cyclical characteristics where its goods and services are needed in the economy no matter the economic situation. However, the IRF graphs show opposite responses to TS, IP, ND, and VIX as found in the long-run relations. Assuming the long-run results are correct, the Utilities prove to move differently than the other industries, opening for a diversification opportunity.

6.3. Limitations and Future Research

This paper serves as an initial study regarding industry returns in Norway. The models are somewhat simplified using one cointegrated equation for the nine VECMs, opening for misspecified models. Further analysis of this topic should use the specified ranks found by the Johansen test for cointegration. In addition, a Granger causality analysis for each model would give a greater picture of the interactions between the variables. Also, the models might not capture all the macroeconomic relationships as only six variables are included. Additional variables could be a default premium variable, consumption, money supply, or the EUR/NOK exchange rate.

This thesis focuses mainly on the relations between the industries and the macroeconomic variables, and not between only the industries or only the macroeconomic variables. Future research could dig deeper into the dynamic between the industries. If they are cointegrated, the diversification benefits could decrease. Maybe a diversification strategy between Nordic countries would show greater diversification benefits? Thus, a more comprehensive study including other countries could describe the potential for international industry diversification.

Lastly, further analysis of the dynamics of each industry relating to business cycles could be of interest. In this study, the industries are commented to be either cyclical or non-cyclical, but relations to actual cyclical periods are not studied. Dividing the analysis into cycles could give greater insight into their actual behavior during expansions or recessionary periods.

6.4. Conclusion

This paper study the relationships between Norwegian industry portfolios and six macroeconomic variables. The period from January 1997 to December 2016 is analyzed based on monthly observations. Cointegrated equations, indicating long-run relations, are found between the variables and nine of the portfolios, where the multi-factor approach Vector Error Correction Model (VECM) captures these relations. No cointegrated relations are found between the variables and the Energy index, where only the short-run relations are captured using a Vector Autoregression (VAR) approach. The main results show positive short-run relations between TS and six of the industry portfolios, and negative long-run relations with TS and VIX for all, except the Utilities industry. The forecasts for each model are decent but miss monthly deviations. The majority of portfolios respond with a permanent, negative effect to unexpected shocks in TS and VIX. Shocks to IP and ND get the least response. For the other variables, the industries respond differently. The differences between the industries in short- and long-run relationships and responses to shocks in the macroeconomic variables give portfolio managers diversification opportunities. By examining the relationships between macroeconomic factors and different Norwegian industries, this thesis fills a gap in the literature by addressing the importance of industry diversification and extending the current research on macroeconomic factors and the Norwegian market as a whole.

References

Barrows, C. W., & Naka, A. (1994). Use of macroeconomic variables to evaluate selected hospitality stock returns in the us. *International Journal of Hospitality Management*, *13*, 119–128.

Berman, J., & Pfleeger, J. (1997). Which industries are sensitive to business cycles. *Monthly Lab. Rev.*, *120*, 19.

Bjørnland, H. C., & Thorsrud, L. A. (2014). *Applied time series for macroeconomics*. Gyldendal Akademisk.

Bugge, S. A., Guttormsen, H. J., Molnár, P., & Ringdal, M. (2016). Implied volatility index for the norwegian equity market. *International Review of Financial Analysis*, *47*, 133–141.

Cavaglia, S., Brightman, C., & Aked, M. (2000). The increasing importance of industry factors. *Financial Analysts Journal*, *56*, 41–54.

Cboe (2019). Cboe vix. URL: `http://www.cboe.com/vix`.

Chen, N.-F. (1991). Financial investment opportunities and the macroeconomy. *The Journal of Finance*, *46*, 529–554.

Chen, N.-F., Roll, R., & Ross, S. A. (1986). Economic forces and the stock market. *Journal of business*, (pp. 383–403).

Cheung, Y.-W., & Lai, K. S. (1993). Finite-sample sizes of johansen's likelihood ratio tests for cointegration. *Oxford Bulletin of Economics and statistics*, *55*, 313–328.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American statistical association*, *74*, 427–431.

Dwyer Jr, G. P., & Wallace, M. S. (1992). Cointegration and market efficiency. *Journal of International Money and Finance*, *11*, 318–327.

Eliassen, R., & Vik, H. (2010). Langsiktige likevektsforhold mellom oslo børs og utvalgte makrovariabler. *Master Thesis*, .

Engle, R. F., & Granger, C. W. (1987). Co-integration and error correction: representation, estimation, and testing. *Econometrica: journal of the Econometric Society*, (pp. 251–276).

Giot, P. (2005). Relationships between implied volatility indices and stock index returns. *Journal of Portfolio Management*, *31*, 92–100.

Gjerde, Ø., & Saettem, F. (1999). Causal relations among stock returns and macroeconomic variables in a small, open economy. *Journal of International Financial Markets, Institutions and Money*, *9*, 61–74.

Granger, C. J. (1986). Developments in the study of cointegrated economic variables. *Oxford Bulletin of economics and statistics*, *48*, 213–228.

Hamao, Y. (1988). An empirical examination of the arbitrage pricing theory: Using japanese data. *Japan and the World economy*, *1*, 45–61.

Hamilton, J. D. (1994). *Time series analysis*. Princeton University Press.

Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of economic dynamics and control*, *12*, 231–254.

Johansen, S. (1995). *Likelihood-based interference in cointegrated vector autoregressive models*. Oxford University Press.

Kavussanos, M. G., Marcoulis, S. N., & Arkoulis, A. G. (2002). Macroeconomic factors and international industry returns. *Applied Financial Economics*, *12*, 923–931.

Kwon, C. S., & Shin, T. S. (1999). Cointegration and causality between macroeconomic variables and stock market returns. *Global Finance Journal*, *10*, 71–81.

Liew, V. K.-S. (2004). Which lag length selection criteria should we employ?, .

Lütkepohl, H. (2005). *New introduction to multiple time series analysis*. Springer Science & Business Media.

Macrobond (2019). Seasonal adjustment census x-13. URL: `https://help.macrobond.com/analyses/filters/seasonaladjustmentx13/`.

Malkiel, B. G., & Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The journal of Finance*, *25*, 383–417.

Maysami, R. C., Loo, S., & Koh, T. (2004). Co-movement among sectoral stock market indices and cointegration among dually listed companies. *Jurnal Pengurusan*, *23*, 33–52.

Mukherjee, T. K., & Naka, A. (1995). Dynamic relations between macroeconomic variables and the japanese stock market: an application of a vector error correction model. *Journal of Financial Research*, *18*, 223–237.

NorwegianPetroleum (2019). Exports of oil and gas. URL: `https://www.norskpetroleum.no/en/production-and-exports/exports-of-oil-and-gas/`.

Ødegaard, B. A. (2018). Empirics of the oslo stock exchange. asset pricing results. 1980–2017., .

Petersen, B., & Strongin, S. (1996). Why are some industries more cyclical than others? *Journal of Business & Economic Statistics*, *14*, 189–198.

Poon, S., & Taylor, S. J. (1991). Macroeconomic factors and the uk stock market. *Journal of Business Finance & Accounting*, *18*, 619–636.

Rongved, H., & Solberg, S. (2018). Dynamic relations between the norwegian stock market and macroeconomic variables. *Master Thesis*, .

Sims, C. A. (1980). Macroeconomics and reality. *Econometrica: journal of the Econometric Society*, (pp. 1–48).

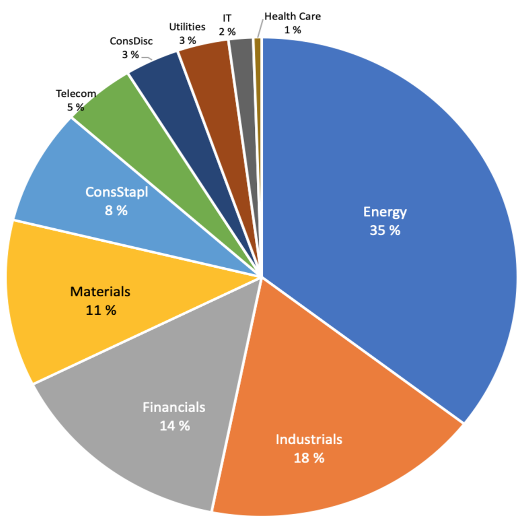
SSB (2019). Index of industrial production. URL: `https://www.ssb.no/en/pii`.

StatisticsNorway (2018). Norges viktigste handelspartnere. URL: `https://www.ssb.no/utenriksokonomi/artikler-og-publikasjoner/norges-viktigste-handelspartnere`.

Whaley, R. E. (2000). The investor fear gauge. *Journal of Portfolio Management*, *26*, 12.

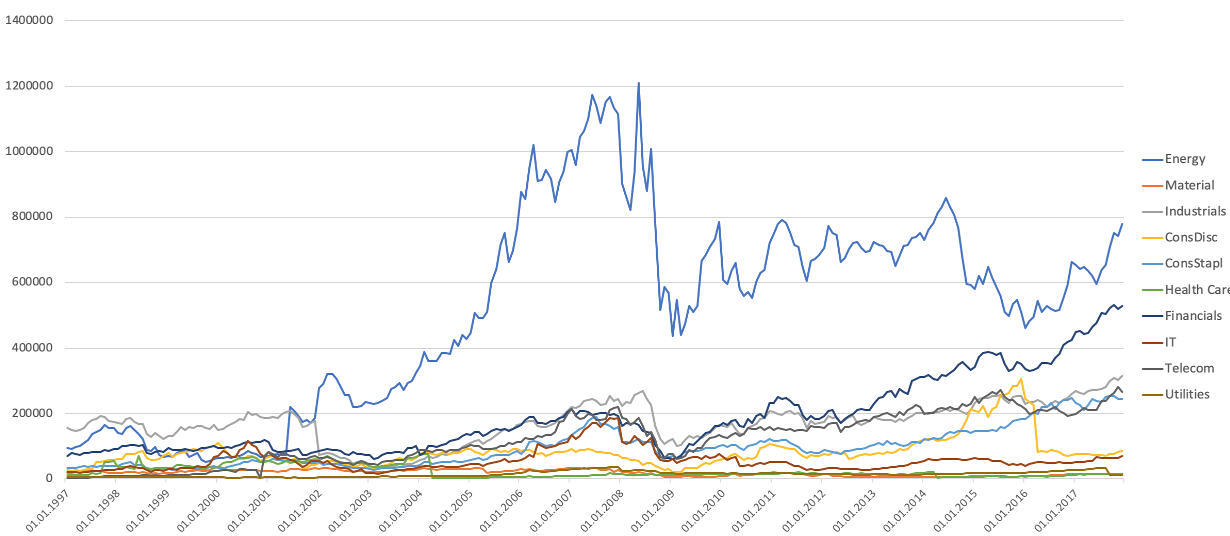
Appendix A. Data

Figure A.1: OSEAX by Sector



Oslo Stock Exchange All-Share Index by Sector as of 03.05.19. Compared by Amount (MNOK).

Figure A.2: Time Series of Portfolio Market Values



Line plot with market values of each industry portfolio in the period 1997M1-2017M12.

Table A1: Subgroups

Energy	Materials	Industrials
Energy Equipment & Services Oil, Gas & Consumable Fuels	Chemicals Construction Materials Containers & Packaging Metals & Mining Paper & Forest Products	Capital Goods Commercial & Professional Services Transportation
Consumer Discretionary	**Consumer Staples**	**Health Care**
Automobiles & Components Consumer Durables & Apparel Consumer Services Retailing	Food & Staples Retailing Food, Beverage & Tobacco Household & Personal Products	Health Care Equipment & Services Pharmaceuticals, Biotechnology & Life Sciences
Financials	**Information Technology**	**Utilities**
Banks Diversified Financials Insurance	Software & Services Technology Hardware & Equipment Semiconductors & Semiconductor Equipment	Electric Utilities Gas Utilities Multi-Utilities Water Utilities Independent Power & Renewable Electricity Producers
Telecom		
Telecommunication Services Media & Entertainment		

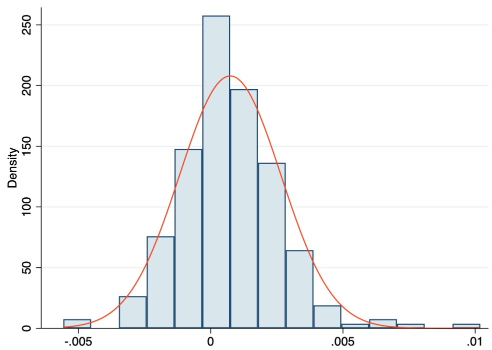
Subgroups within each industry described by GICS.

Table A2: Correlation Matrix of Industry Portfolios in First Difference

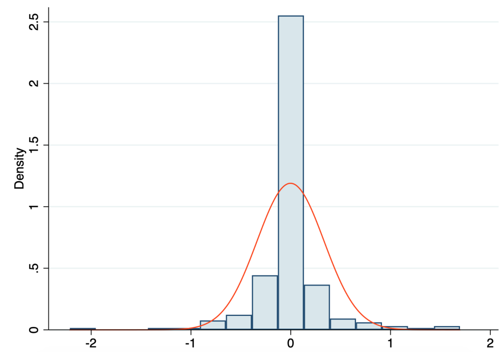
Variable	Energy	Materials	Industrials	ConsDisc	ConsStapl	Health Care	Financials	IT	Telecom	Utilities
Energy	1.0000									
Materials	0.2659	1.0000								
Industrials	0.6961	0.3591	1.0000							
ConsDisc	0.2855	0.3897	0.5213	1.0000						
ConsStapl	0.5333	0.3284	0.6112	0.4356	1.0000					
Health Care	0.3783	0.2629	0.4365	0.2861	0.3994	1.0000				
Financials	0.5321	0.3918	0.6629	0.5367	0.6029	0.3459	1.0000			
IT	0.4767	0.2763	0.5772	0.4293	0.5160	0.3881	0.4413	1.0000		
Telecom	0.3798	0.2030	0.4783	0.3668	0.3532	0.4394	0.4058	0.5534	1.0000	
Utilities	0.3481	0.2999	0.4463	0.2926	0.4858	0.4106	0.4281	0.4144	0.3296	1.0000

Pairwise correlations coefficients of industry indices in First Difference in the period 1997M1-2017M12. All correlations are significant at 1% level.

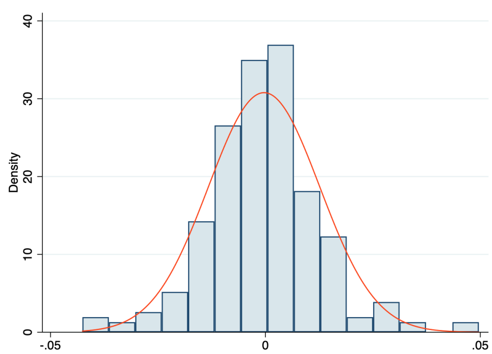
Figure A.3: Histograms of Macroeconomic Variables in First Difference



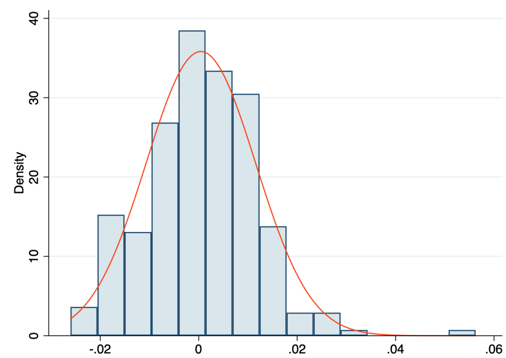
(a) CPI



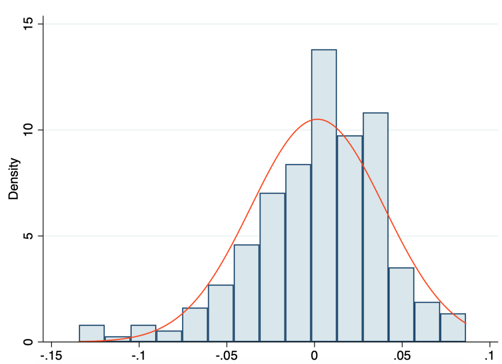
(b) Term Structure



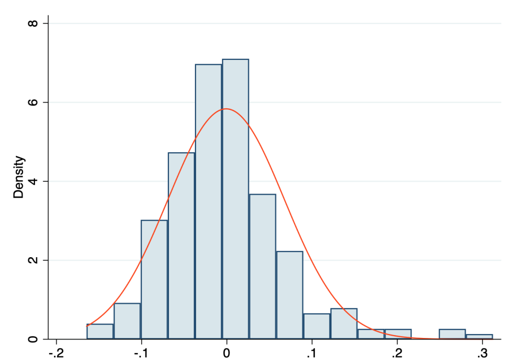
(c) Industrial Production



(d) NOK/USD



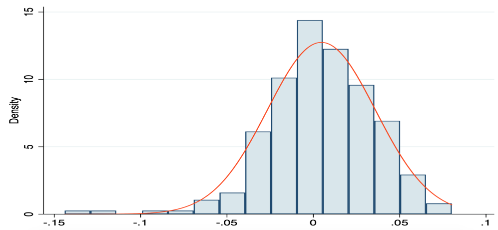
(e) Oil Price



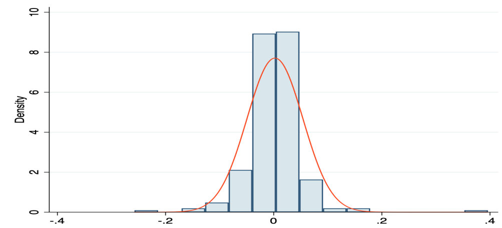
(f) VIX

Histograms with normal distribution for the macroeconomic variables in First Difference. CPI = consumer price index, TS = term spread, IP = industrial production, ND = USD/NOK exchange rate, OP = oil price, VIX = volatility index. Sample period: 1997M1-2016M12.

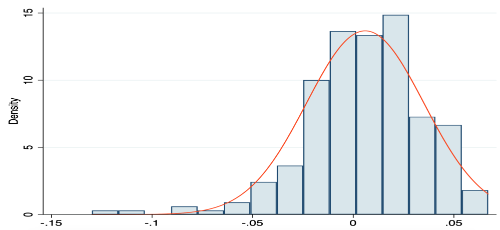
Figure A.4: Histograms for Industry Portfolios in First Difference.



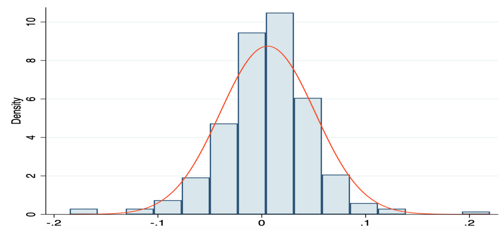
(a) Energy



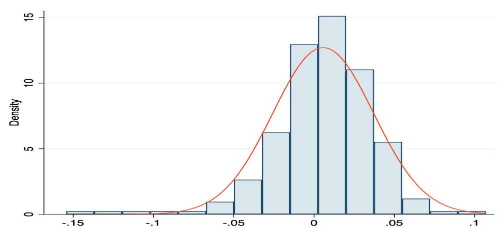
(b) Materials



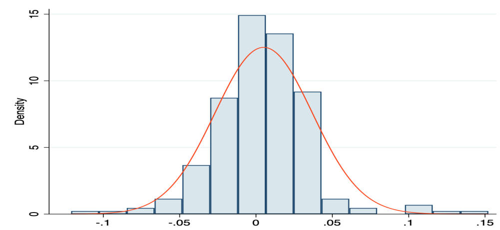
(c) Industrials



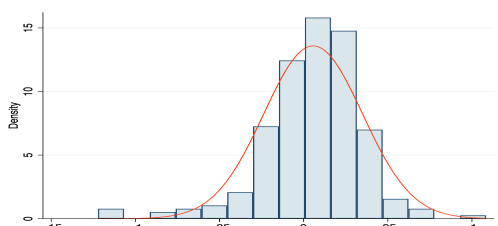
(d) Consumer Discretionary



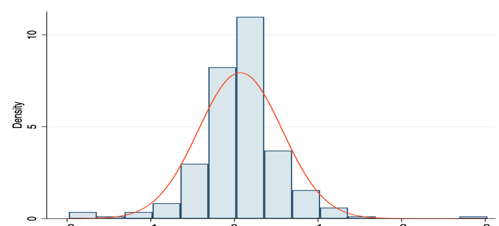
(e) Consumer Staples



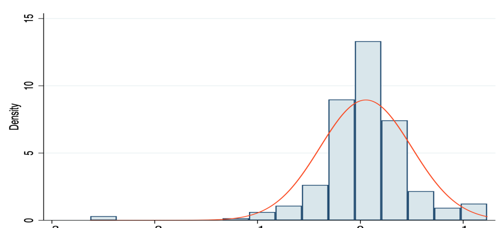
(f) Health Care



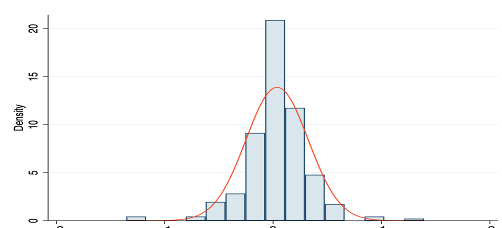
(g) Financials



(h) IT



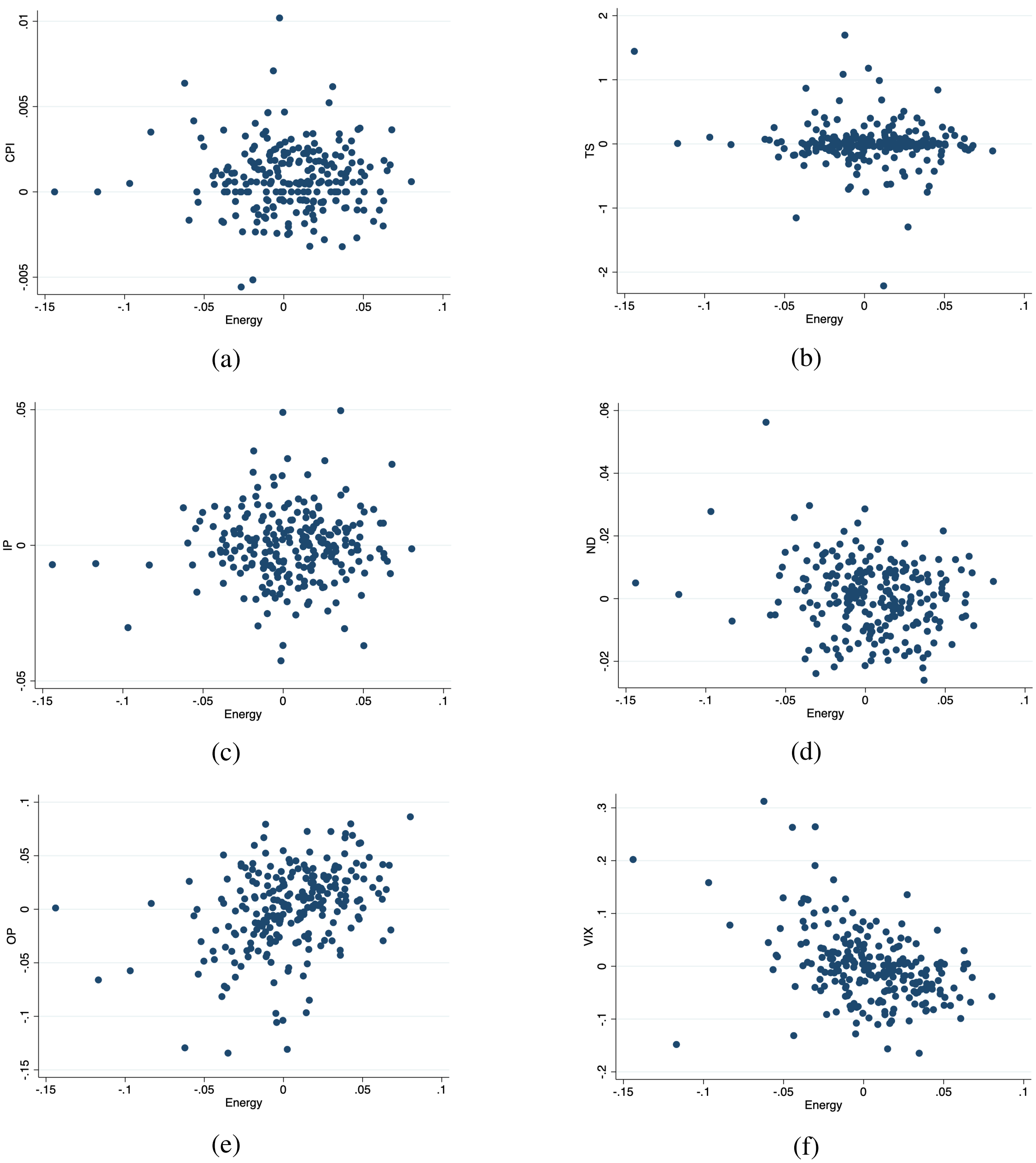
(i) Telecom



(j) Utilities

Histograms with normal distribution for industry indices in First Difference. Sample period: 1997M1-2016M12.

Figure A.5: Scatter plots of Energy Portfolio and the Macroeconomic Variables



Scatter plots of Energy index and the macroeconomic variables, all in First Difference. From the top left we have CPI = consumer price index, TS = term spread, IP = industrial production, ND = USD/NOK exchange rate, OP = oil price, VIX = volatility index. Sample period: 1997M1-2016M12.

Appendix B. Detailed Results

Figure B.6: Johansen Cointegration Tests

Johansen tests for cointegration
Trend: constant — Number of obs = 238
Sample: 1997m3 - 2016m12 — Lags = 2

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	56	-3035.5989	.	121.1216*	124.24
1	69	-3016.4681	0.14851	82.8598	94.15
2	80	-2999.8486	0.13035	49.6209	68.52
3	89	-2989.0542	0.08672	28.0321	47.21
4	96	-2982.8428	0.05086	15.6093	29.68
5	101	-2977.2659	0.04578	4.4555	15.41
6	104	-2975.9071	0.01135	1.7379	3.76
7	105	-2975.0382	0.00728		

(a) Energy VAR

Johansen tests for cointegration
Trend: constant — Number of obs = 238
Sample: 1997m3 - 2016m12 — Lags = 2

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	56	-2846.4558	.	172.7744	124.24
1	69	-2806.3203	0.28629	92.5033*	94.15
2	80	-2787.5806	0.14570	55.0239	68.52
3	89	-2775.3824	0.09743	30.6275	47.21
4	96	-2766.1837	0.07439	12.2301	29.68
5	101	-2761.6547	0.03734	3.1722	15.41
6	104	-2760.1693	0.01240	0.2013	3.76
7	105	-2760.0687	0.00085		

(b) Materials VECM

Johansen tests for cointegration
Trend: constant — Number of obs = 238
Sample: 1997m3 - 2016m12 — Lags = 2

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	56	-3147.265	.	141.4029	124.24
1	69	-3123.015	0.18436	92.9029*	94.15
2	80	-3106.4388	0.13003	59.7505	68.52
3	89	-3093.551	0.10264	33.9748	47.21
4	96	-3085.8883	0.06236	18.6495	29.68
5	101	-3080.5171	0.04413	7.9071	15.41
6	104	-3077.3138	0.02656	1.5004	3.76
7	105	-3076.5636	0.00628		

(c) Industrials VECM

Johansen tests for cointegration
Trend: constant — Number of obs = 238
Sample: 1997m3 - 2016m12 — Lags = 2

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	56	-3312.5373	.	127.1988	124.24
1	69	-3293.0125	0.15132	88.1491*	94.15
2	80	-3274.6635	0.14289	51.4512	68.52
3	89	-3262.5901	0.09648	27.3044	47.21
4	96	-3255.1567	0.06055	12.4376	29.68
5	101	-3250.6769	0.03695	3.4779	15.41
6	104	-3249.3386	0.01118	0.8014	3.76
7	105	-3248.9379	0.00336		

(d) Consumer Discretionary VECM

Johansen tests for cointegration
Trend: constant — Number of obs = 238
Sample: 1997m3 - 2016m12 — Lags = 2

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	56	-3109.387	.	177.8318	124.24
1	69	-3076.0615	0.24425	111.1808	94.15
2	80	-3056.821	0.14929	72.6997	68.52
3	89	-3042.689	0.11198	44.4359*	47.21
4	96	-3031.1162	0.09267	21.2901	29.68
5	101	-3025.7301	0.04425	10.5180	15.41
6	104	-3021.0568	0.03851	1.1714	3.76
7	105	-3020.4711	0.00491		

(e) Consumer Staples VECM

Johansen tests for cointegration
Trend: constant — Number of obs = 238
Sample: 1997m3 - 2016m12 — Lags = 2

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	56	-3030.2273	.	153.6670	124.24
1	69	-3004.6614	0.19333	102.5352	94.15
2	80	-2987.0168	0.13781	67.2459*	68.52
3	89	-2973.3269	0.10867	39.8661	47.21
4	96	-2960.2989	0.10370	13.8101	29.68
5	101	-2955.7107	0.03782	4.6337	15.41
6	104	-2953.943	0.01474	1.0983	3.76
7	105	-2953.3938	0.00460		

(f) Health Care VECM

Johansen tests for cointegration
Trend: constant — Number of obs = 238
Sample: 1997m3 - 2016m12 — Lags = 2

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	56	-3145.5304	.	142.2732	124.24
1	69	-3123.6051	0.16827	98.4225	94.15
2	80	-3104.7699	0.14639	60.7522*	68.52
3	89	-3092.0151	0.10164	35.2426	47.21
4	96	-3082.9222	0.07356	17.0568	29.68
5	101	-3077.5333	0.04428	6.2789	15.41
6	104	-3074.9959	0.02110	1.2041	3.76
7	105	-3074.3938	0.00505		

(g) Financials VECM

Johansen tests for cointegration
Trend: constant — Number of obs = 238
Sample: 1997m3 - 2016m12 — Lags = 2

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	56	-3402.9348	.	138.5515	124.24
1	69	-3378.9597	0.18247	90.6013*	94.15
2	80	-3362.6816	0.12785	58.0451	68.52
3	89	-3349.19	0.10718	31.0620	47.21
4	96	-3342.109	0.05777	16.9000	29.68
5	101	-3337.5304	0.03775	7.7427	15.41
6	104	-3334.4107	0.02587	1.5034	3.76
7	105	-3333.659	0.00630		

(h) IT VECM

Johansen tests for cointegration
Trend: constant — Number of obs = 238
Sample: 1997m3 - 2016m12 — Lags = 2

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	56	-3205.9986	.	132.8437	124.24
1	69	-3185.9738	0.15488	92.7941*	94.15
2	80	-3167.8269	0.14144	56.5001	68.52
3	89	-3155.6944	0.09693	32.2352	47.21
4	96	-3147.6182	0.06562	16.0828	29.68
5	101	-3141.4957	0.05015	3.8377	15.41
6	104	-3139.8258	0.01393	0.4979	3.76
7	105	-3139.5768	0.00209		

(i) Telecom VECM

Johansen tests for cointegration
Trend: constant — Number of obs = 238
Sample: 1997m3 - 2016m12 — Lags = 2

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	56	-2888.3643	.	144.5324	124.24
1	69	-2862.0961	0.19808	91.9960*	94.15
2	80	-2845.4147	0.13080	58.6333	68.52
3	89	-2830.6095	0.11699	29.0228	47.21
4	96	-2823.1328	0.06090	14.0696	29.68
5	101	-2818.749	0.03617	5.3019	15.41
6	104	-2816.5816	0.01805	0.9670	3.76
7	105	-2816.0981	0.00405		

(j) Utilities VECM

Johansen test for cointegration for all ten models, one for each industry index in combination with the six macroeconomic variables. Variables in Levels.

Figure B.7: Lagrange-Multiplier Tests

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	**52.1690**	**49**	**0.35178**
2	**59.1662**	**49**	**0.15156**

H0: no autocorrelation at lag order

(a) Energy VAR

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	**54.7078**	**49**	**0.26685**
2	**58.4714**	**49**	**0.16661**

H0: no autocorrelation at lag order

(b) Materials VECM

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	**44.2344**	**49**	**0.66640**
2	**52.4203**	**49**	**0.34281**

H0: no autocorrelation at lag order

(c) Industrials VECM

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	**60.6991**	**49**	**0.12198**
2	**61.9166**	**49**	**0.10185**

H0: no autocorrelation at lag order

(d) Consumer Discretionary VECM

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	**45.9793**	**49**	**0.59634**
2	**51.6208**	**49**	**0.37173**

H0: no autocorrelation at lag order

(e) Consumer Staples VECM

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	**47.5368**	**49**	**0.53257**
2	**51.9671**	**49**	**0.35907**

H0: no autocorrelation at lag order

(f) Health Care VECM

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	**51.3601**	**49**	**0.38139**
2	**56.9655**	**49**	**0.20290**

H0: no autocorrelation at lag order

(g) Financials VECM

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	**52.7833**	**49**	**0.33006**
2	**64.4101**	**49**	**0.06892**

H0: no autocorrelation at lag order

(h) IT VECM

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	**48.5953**	**49**	**0.48944**
2	**60.3948**	**49**	**0.12746**

H0: no autocorrelation at lag order

(i) Telecom VECM

Lagrange-multiplier test

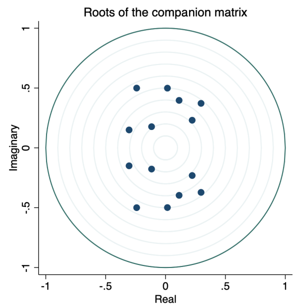
lag	chi2	df	Prob > chi2
1	**42.0710**	**49**	**0.74784**
2	**55.3735**	**49**	**0.24681**

H0: no autocorrelation at lag order

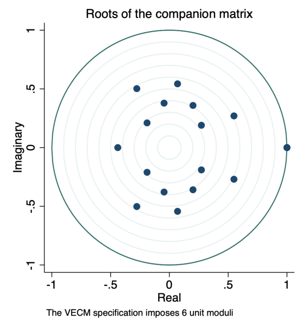
(j) Utilities VECM

Lagrange-Multiplier Test for all ten VECMs, meaning each industry in combination with the macroeconomic variables, with two lags. Sample period: 1997M1-2016M12. H_0 = no autocorrelation at lag order.

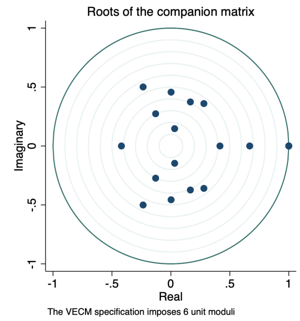
Figure B.8: Eigenvalue Stability Conditions



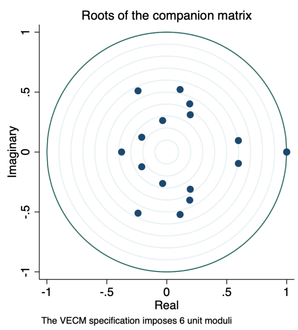
(a) Energy VAR



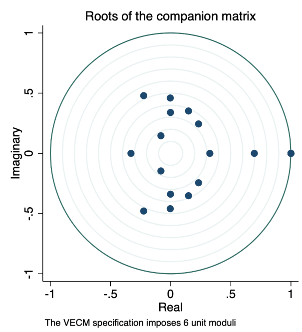
(b) Materials VECM



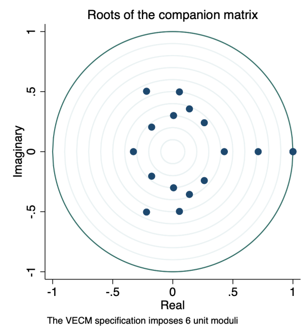
(c) Industrials VECM



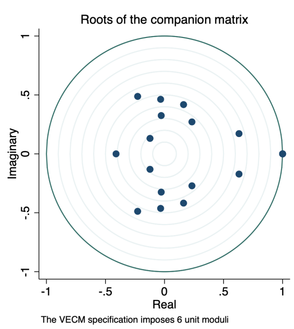
(d) ConsDisc VECM



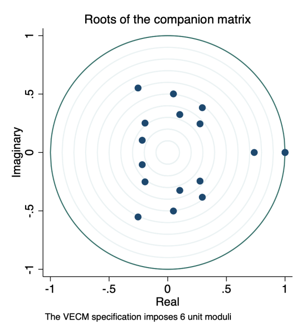
(e) Consumer Staples VECM



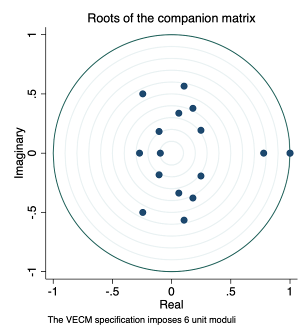
(f) Health Care VECM



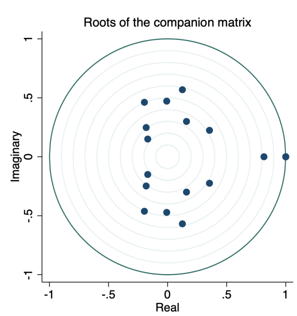
(g) Financials VECM



(h) IT VECM



(i) Telecom VECM



(j) Utilities VECM

Eigenvalue Stability Conditions for all ten models, meaning each industry in combination with the macroeconomic variables, with two lags. Sample period: 1997M1-2016M12. All models are stable. For the VAR all eigenvalues are less than one. For the VECMs they have $K-r$=7-1=6 unit eigenvalues, while the remaining eigenvalues are less than zero.

Figure B.9: Jarque-Bera Test for Normally Distributed Disturbances

Equation	chi2	df	Prob > chi2
DLenergy	26.414	2	0.00000
DLCPI	68.385	2	0.00000
DLTS	663.543	2	0.00000
DLIP	31.894	2	0.00000
DLND	0.161	2	0.92258
DLOP	13.497	2	0.00117
DLVIX	30.644	2	0.00000
ALL	834.538	14	0.00000

(a) Energy VAR

Equation	chi2	df	Prob > chi2
D_Lmaterial	187.708	2	0.00000
D_LCPI	70.083	2	0.00000
D_LTS	523.879	2	0.00000
D_LIP	34.643	2	0.00000
D_LND	1.298	2	0.52254
D_LOP	23.241	2	0.00001
D_LVIX	44.242	2	0.00000
ALL	885.093	14	0.00000

(b) Materials VECM

Equation	chi2	df	Prob > chi2
D_Lindustrials	47.089	2	0.00000
D_LCPI	60.887	2	0.00000
D_LTS	581.024	2	0.00000
D_LIP	34.498	2	0.00000
D_LND	0.100	2	0.95145
D_LOP	22.906	2	0.00001
D_LVIX	8.115	2	0.01729
ALL	754.619	14	0.00000

(c) Industrials VECM

Equation	chi2	df	Prob > chi2
D_Lconsdisc	40.553	2	0.00000
D_LCPI	80.639	2	0.00000
D_LTS	451.300	2	0.00000
D_LIP	36.521	2	0.00000
D_LND	3.804	2	0.14924
D_LOP	20.522	2	0.00003
D_LVIX	16.126	2	0.00031
ALL	649.466	14	0.00000

(d) Consumer Discretionary VECM

Equation	chi2	df	Prob > chi2
D_Lconsstapl	223.617	2	0.00000
D_LCPI	81.428	2	0.00000
D_LTS	520.413	2	0.00000
D_LIP	35.637	2	0.00000
D_LND	0.194	2	0.90747
D_LOP	17.638	2	0.00015
D_LVIX	13.783	2	0.00102
ALL	892.710	14	0.00000

(e) Consumer Staples VECM

Equation	chi2	df	Prob > chi2
D_Lhealth	88.173	2	0.00000
D_LCPI	64.253	2	0.00000
D_LTS	486.243	2	0.00000
D_LIP	39.934	2	0.00000
D_LND	3.978	2	0.13681
D_LOP	13.935	2	0.00094
D_LVIX	21.932	2	0.00002
ALL	718.449	14	0.00000

(f) Health Care VECM

Equation	chi2	df	Prob > chi2
D_Lfinancials	78.383	2	0.00000
D_LCPI	64.391	2	0.00000
D_LTS	568.218	2	0.00000
D_LIP	32.555	2	0.00000
D_LND	0.082	2	0.95976
D_LOP	17.684	2	0.00014
D_LVIX	14.929	2	0.00057
ALL	776.242	14	0.00000

(g) Financials VECM

Equation	chi2	df	Prob > chi2
D_Lit	364.645	2	0.00000
D_LCPI	65.109	2	0.00000
D_LTS	539.982	2	0.00000
D_LIP	25.821	2	0.00000
D_LND	1.664	2	0.43522
D_LOP	17.183	2	0.00019
D_LVIX	28.187	2	0.00000
ALL	1042.591	14	0.00000

(h) IT VECM

Equation	chi2	df	Prob > chi2
D_Ltelecom	431.152	2	0.00000
D_LCPI	81.526	2	0.00000
D_LTS	516.433	2	0.00000
D_LIP	32.365	2	0.00000
D_LND	0.302	2	0.85983
D_LOP	7.523	2	0.02325
D_LVIX	47.562	2	0.00000
ALL	1116.863	14	0.00000

(i) Telecom VECM

Equation	chi2	df	Prob > chi2
D_Lutilities	180.559	2	0.00000
D_LCPI	67.149	2	0.00000
D_LTS	559.066	2	0.00000
D_LIP	34.767	2	0.00000
D_LND	0.404	2	0.81729
D_LOP	15.160	2	0.00051
D_LVIX	48.424	2	0.00000
ALL	905.528	14	0.00000

(j) Utilities VECM

Jarque-Bera test for normally distributed disturbances for all the models, meaning each industry in combination with the macroeconomic variables, with two lags. Sample period: 1997M1-2016M12. H_0 = the disturbances in the VECM are normally distributed.

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