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Forecasting Norwegian GDP

An Empirical Analysis of Categorized Macroeconomic Data

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NORWEGIAN SCHOOL OF ECONOMICS

Abstract

The topic of this master thesis is forecasting of Norwegian quarterly GDP growth. We aim to research whether a dataset of many variables can forecast Norwegian GDP growth accurate in the period 2014q2 to 2018q1, with forecast horizons of 4-quarters, 8-quarters and 12-quarters. Accuracy will in this thesis be defined as minimizing the root mean square error. Further, we are analyzing which group of categorized variables, based on economic content, that forecast GDP growth most accurately. The forecast is performed based on 148 variables, where we categorize the variables based on economic content, and then perform a Principal Component Analysis within each category. Finally, we investigate whether an index of leading indicators based on the Norwegian economy can forecast accurately. The index is created using the same method as The Conference Board Leading Economic Index for the United States, using corresponding variables for the Norwegian economy.

We find that using Principal Component Analysis in forecasting is able to outperform the benchmark of an Autoregressive model. Further, the analysis shows that a category containing production measures forecasts most accurate for all horizon. The forecast model with all 148 variables included performs second most accurate forecasts. Further, the findings suggest that the created index of leading economic indicators for the Norwegian economy is not accurate in terms of forecasting Norwegian GDP growth in the period 2014q2 to 2018q1.

Acknowledgments

This master thesis was written during the spring 2019 as a part of our Master of Science degree in Economics and Business Administration at NHH Norwegian School of Economics.

We wanted to apply the theoretical fundaments the courses at NHH has given us, and the choice of topic reflects both personal and academic interests. We have especially found the courses *Business Cycle Analysis* and *Empirical Methods and Applications in Macroeconomics and Finance* interesting, and thus we found it natural to choose a topic within the fields of these courses.

The research process has been challenging, exciting and educational, and we have gained deep insights in the exciting field that is forecasting. It has been very educative to work together towards a common goal, and the research has additionally increased our knowledge and interests on the topic. We hope that the research will contribute with useful insights for anyone with interests in forecasting.

We would like to thank our supervisor, Professor Gernot Peter Doppelhofer for great support during this process. Insightful discussions and inputs have contributed to improve the quality of the research significantly.

Norwegian School of Economics

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1. Introduction

Forecasting in economics is the process of making predictions about future conditions. Forecasts can be done on broad indicators, such as gross domestic product (GDP), inflation or unemployment, or on more specific terms, such as sectors of the economy or a firm. One of the factors when Norges Bank is deciding the key policy rate is predictions of GDP. It is imperative that the government considers future GDP in order to decide whether to pursue an expansionary or contractionary fiscal policy. For instance if GDP is predicted to decline in the future, the government can pursue to stimulate the economy by increasing spending. Therefore, to make accurate forecasts is imperative in order to make good decisions.

Many variables affect Norwegian GDP, and these variables are varied in terms of economic content. Thus, it is challenging to decide which variables that will forecast good prior to performing the actual forecasts. Another problem of forecasting using many variables is to obtain parsimonious models. We wanted to find a method that could handle these challenges. The method we selected is called *Principal Component Analysis*. Principal Component Analysis compresses many variables into fewer, uncorrelated components which captures most of the variation from the original variables. This makes it possible to analyze large datasets while keeping the models parsimonious.

In this master thesis, we will use this method to make accurate mid- to long-term forecasts of Norwegian economic activity, more specific Norwegian quarterly GDP growth. Mid- to long-term is in this paper defined as forecast horizons of 4-quarters, 8-quarters and 12-quarters. These horizons were chosen because government- and central bank policies has the greatest impact in this time span. Thus, the forecasts in these horizons are relevant to consider when making policy decisions. When new policies are implemented, it takes several quarters before the economy is impacted, hence 4-quarters is chosen as the shortest forecast horizon. Moreover, these policy changes will also affect the economy at longer horizons. Therefore, we included 8-quarters and 12-quarters forecast horizons.

The analysis will be conducted using 148 variables with observations in the period of 1995 to 2018. The methodology in the thesis targets to answer three empirical questions, which we will go through next.

Can a dataset containing many variables forecast Norwegian quarterly GDP growth accurate in a mid- to long-term forecast horizon in the period 2014q2 to 2018q1?

Which category of variables, based on economic content, can forecast Norwegian GDP growth accurate mid- to long-term?

Accurate implies minimizing the RMSE, and the target is to outperform the benchmark of an *Autoregressive model*, where GDP growth is projected on its own lags. We will also construct a second benchmark of a Random walk, where the predicted value is equal to the last actual observed value. Outperforming of the benchmark models implies obtaining a lower average RMSE than the benchmarks.

The period from 2014q2 to 2018q1 is the forecast period, while 1995q3 to 2014q1 is the model estimation period. The forecast method used, is called *Pseudo out of sample forecasting.* The method simulates standing at a given time t where the models is estimated using only data available at that time, and forecasting until period t+h, where h represents the forecast horizons. This is repeated for all dates in the forecast period.

To answer the first research question, we have performed a Principal Component Analysis using all variables in the dataset, before forecasting. Prior to performing the analysis for the second research question, the variables are categorized based on economic content. The categories are *Employment, Export & Import, Foreign Financials, Government Statistics, Housing, Interest Rates & Swaps, Money & Credit, Norwegian Financials, Other Business Statistics and Production.* Each variable is only included in one category. The categories are separately analyzed with Principal Component Analysis, and the output is used to forecast. The focus will be on how each category forecasts Norwegian GDP growth, and not how each variable contributes to forecasting.

Furthermore, we want to analyze whether leading indicators can forecast Norwegian GDP growth accurate. Leading indicators is often used to predict general direction of the economy, i.e. whether we will have positive or negative growth in the short term. However, we find it interesting to see whether these types of variables can be used to forecast GDP growth accurate. This will be done by constructing a leading economic index for the Norwegian economy, and performing a forecast based on this index.

Can an index of leading economic indicators forecast Norwegian quarterly GDP growth accurate?

This index of leading economic indicators will be created by replicating the method used by The Conference Board Leading Economic Index (LEI) for the US economy. This implies that the index will be used in forecasting without the usage of Principal Component Analysis. The LEI is considered a reliable indicator of where the US economy is headed in the short term. We want to research whether a similar index for the Norwegian economy is able forecast Norwegian GDP growth accurately. The construction of the leading index for the Norwegian economy is described in subchapter 5.3.

The paper is structured as follows; chapter 2 will discuss the related literature and give an overview of what we expect from this thesis' analysis based on the related literature. In chapter 3, we will present the models used for estimations. Chapter 4 gives an overview of the data, how it is collected and transformed. Chapter 5 presents the methodology used for answering the empirical research questions. The results from the analysis will be shown in chapter 6, and the results will be discussed and analyzed further in chapter 7. Chapter 8 will conclude the paper.

2. Related literature

This chapter discusses the literature related to the thesis. The literature chosen in this chapter are forecasting using pseudo out of sample forecasts. Further, the papers are constructing the forecast models using Principal Component Analysis or the dynamic factor model. The dynamic factor model is a derived version of Principal Component Analysis, which makes it more optimized for prediction of the present or the very near future (Doz, Giannone, & Reichlin, 2012). The papers are using different datasets to forecast different macroeconomic variables. We will discuss the relevant papers methodology and results. Finally, we will discuss the relevance of the papers to this thesis, and what we expect to find in this thesis' in terms of the related literature. We are using three papers as key literature; *Forecasting inflation* by Stock & Watson (1999), *Forecasting Macroeconomic Variables using Disaggregate Survey Data* by Martinsen, Ravazzolo and Wulfsberg (2014) and *Nowcasting Norwegian GDP: The Role of Asset Prices in a Small Open Economy* by Knut Are Aastveit and Tørres G. Trovik (2012).

Forecasting inflation by Stock and Watson (1999) is an influential paper in the field of forecasting, and was published in the Journal of Monetary Economics. The journal is peer reviewed, and considered to be prestigious. Stock and Watson successfully used Principal Component Analysis in forecasting US inflation, and therefore we find the paper relevant for comparison. The papers by Aastveit and Trovik (2012) and Martinsen et al. (2014) are research papers written in cooperation with Norges Bank. The papers performed similar analyses as this thesis in terms of methodology and forecast horizons, for the Norwegian economy. Thus, we find it interesting to compare our thesis to these papers.

Stock and Watson (1999) targets to forecast inflation at the 12-months horizon using an extended Phillips curve with many variables of real economic measures. They solved the problem regarding parsimony, using Principal Component Analysis. The results show that the usage of Principal Component Analysis in their forecasting produces good results. They significantly improved the generalized Phillips curve benchmark, and the best models consisted of real aggregate activity measures, and the model with all variables. Forecasting using all variables performs well, but the real aggregate activity measures forecasts inflation most accurately.

Other papers have targeted to nowcast and forecast Norwegian GDP, such as Aastveit and Trovik (2012) and Martinsen et al. (2014). Nowcasting is predicting the present or the very near future of an economic measure. Aastveit and Trovik (2012) researched the role of asset prices in nowcasting and forecasting of Norwegian GDP, using a dynamic factor model. Martinsen et.al (2014) also used a dynamic factor model. However, the target was to construct factor models based on survey data to forecast macroeconomic variables such as inflation and GDP.

Aastveit and Trovik (2012) analyze 148 variables from a broad spectrum of the Norwegian economy. They find that the most important categories in forecasting at 1-4 quarters horizon is asset prices on Oslo Stock Exchange, Labor market data, and Industrial production indicators. They are all outperforming the benchmark of a Random walk. Martinsen et al. (2014) finds that factor models consisting of surveys outperforms the autoregressive benchmark model in forecasting Norwegian GDP growth at horizons 1-4 quarters.

The mentioned papers all use factor models to compress their large datasets. Further, they use either AR model, Random walk, or a Philips Curve as the benchmark for pseudo out of sample forecasting. In this thesis, we will forecast using a large dataset of a broad spectrum of macroeconomic data, and compress with Principal Component Analysis. Moreover, we will use Autoregressive and Random walk models as benchmarks.

The similar approach as the mentioned papers makes us expect that some categories will be able to outperform the benchmarks in forecasting using Principal Component Analysis, at a 4-quarter horizon. Further, based on Stock and Watson (1999), we expect that the model consisting of factors from all variables, will be an accurate forecast model. Moreover, based on Aastveit and Trovik (2012) and Martinsen et.al (2014), we expect that categories consisting of financial data, labor market data, industrial production measures, and surveys, will perform good in forecasting with the 4-quarter forecast horizon.

3. Theoretical fundament

3.1 Principal Component Analysis

When performing a data analysis with many variables, we can face the problem of variables being correlated. In model estimations, this correlation between variables is called multicollinearity. If this is not accounted for, it can reduce the precision of the coefficient estimates. This problem can be accounted for by using Principal Component Analysis (*PCA*). The idea of a PCA is to reduce the dimensionality of the dataset. The reduction is achieved by transforming the original dataset into a fewer set of factors which explains most of the variation, called *principal components* (Ian T. Jolliffe, 1986). These components are constructed as orthogonal vectors, which implies that all the vectors are perpendicular. Thus, the problem of multicollinearity is accounted for (Ian T. Jolliffe, 1986).

PCA takes p variables $X_1, X_2, \dots, X_p$ and creates linear combinations of these variables where the linear combinations is the principal components. The PCA creates as many components as original variables, and the components will be denoted as $Z_1, Z_2, \dots, Z_p$. The best results from PCA is achieved when the variables are correlated. In this case, a few components will be able to explain a lot of the variance in the data set. In a special case where all variables are uncorrelated prior the PCA, the PCA is not useful (Manly, 2005).

The general covariance matrix C is shown below. The covariance matrix C is based on all the variables in the dataset. The diagonal c_{ii} is the variance of variables X_i, and the off-diagonal values, c_{ij}, is the covariance between variables X_i and X_j. The sum of variance in all the variables is equal to the sum of all variance in the principal components (Manly, 2005).

$$C = \begin{pmatrix} c_{11} & c_{12} & .. & c_{1p} \\ c_{21} & c_{22} & .. & c_{2p} \\ . & . & & . \\ . & . & & . \\ c_{p1} & c_{p2} & .. & c_{pp} \end{pmatrix}$$

The covariance matrix is only useful if the input variables X are expressed in common units. This will make a meaningful relationship between the variables in terms of comparing variances. Thus, the variables need to have a common scale of unit before they are used in the PCA (Manly, 2005). Further, the variables need to be stationary in order to calculate the covariances between X_i and X_j in the matrix C. The reason for transforming to stationarity is to obtain meaningful means and variances between variables, which the covariance is based on (Wooldridge, 2016). Stationarity and the transforming of the variables is described in subchapter 4.2.

$$C = V\Lambda V' = \sum_{i=1}^{p} \lambda_i v_i v_i'$$

Where $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_p \geq 0$

The eigen-decomposition decomposes the covariance matrix C into a set of eigenvalues and eigenvectors, where v_i is the eigenvectors of the matrix C, and λ_p is the eigenvalues (Manly, 2005). The eigenvectors are equivalent to the principal components. In the covariance matrix, the eigenvectors are orthonormal, i.e. uncorrelated and normalized. The eigenvalues explain the variances of the corresponding components Z. The eigenvalues from the covariance matrix C is ordered such that the eigenvalue for component 1 is larger than the eigenvalue for component 2, and so on. This implies that component 1 captures most variance from the variables in the original dataset, component 2 captures second most, and so forth.

In the formula below, we see that the component Z is a linear combination of the different variables, X_1, X_2, … , X_p, and all Z's are orthogonal to each other. v_{ip} is the elements of the eigenvector v_i for each variable X_p, and represents the coefficient. If the elements of the eigenvector are multiplied with the value of the corresponding variable, we obtain the contribution of variable X_p in component Z_i (Manly, 2005).

$$Z_i = v_{i1}X_1 + v_{i2}X_2 + \cdots + v_{ip}X_p$$

When using the components for further estimations, we need to select how many components to use. There are several methods elaborating on how to do this. A rule of thumb is to use all components with an eigenvalue above one (Ian T. Jolliffe, 1986). The reason for this is that a component with an eigenvalue below one explains less than that of one of the original variables. If we put the eigenvalues in a decreasing order, we can for example have components with eigenvalues of 10, 6, 3, 2, 0.9, 0.8, 0.8... In this case, four components should be included, because four of the components have an eigenvalue larger than one.

Another method is to use the proportion of the components to choose the optimal number of components to use. The *proportion* is a percentage measure of how much of the total variation in the dataset is captured by the component. It is calculated as the eigenvalue for the corresponding component divided by the sum of eigenvalues for all components (Manly, 2005). According to Jolliffe (1973), one should choose a cut-off point where the cumulative proportions for the number of components chosen is around 70% - 90%. This implies that the chosen components capture 70% - 90% of the total variation from the original variables.

3.2 The Conference Board Leading Economic Index

In this chapter, we will present The Conference Board Leading Economic Index (LEI) for the US economy. The goal of the index is to give an indication of where the economy is headed forward. The index is decided based on ten key variables, which are chosen based on past performance of indicating up- and downturns in the economy.

The table below shows which variables is included in the Conference LEI for the US economy, and the standardization factor for each variable (The Conference Board, 2019). The standardization factor reflects how much each variable contributes to changes in the index, and is a way of weighting the variables in the index based on inverted volatility. The main idea of the standardization factors is to attach a lower weight to more volatile variables, such that the adjusted rates of changes of variables have the same contribution to the index (Doppelhofer, 2018). The six-step procedure of calculating the LEI are shown in Appendix 4.

Table 1: List of variables and standardization factors in The Conference Board LEI for the US economy

Variables in index	Standardization factor
Average weekly hours. manufacturing	0.280
Average weekly initial claims for unemployment insurance	0.032
Manufacturers' new orders. consumer goods and materials	0.083
ISM new order index	0.159
Manufacturers' new orders. non-defense capital goods excluding aircraft	0.041
Building permits. new private housing units	0.029
Stock prices. S&P500 common stocks	0.040
Leading credit index	0.081
Interest rate spread. 10-year Treasury bonds less federal funds	0.113
Average consumer expectations for business and economic conditions	0.143

Note: Table shows variables included in The Conference Board LEI with corresponding standardization factor. The standardization factor is based on inverse volatility and is a method of weighting the variables in the index.

3.3 Autoregressive model

An autoregressive (AR) model is a model were the independent variables is lagged values of the dependent variable. The number of lags included decides the order of the autoregressive model. For instance, a model with one lag is called a first order AR model; a model with two lags is a second order AR model and so on. Moreover, when forecasting based on an AR model, we only base the forecast on observed historic values of the dependent variable. An AR model is a fairly simple model but will often perform well when forecasting compared to more complicated models (Chan, 2011). The general formula for an AR process, of an order p, is shown below (Bjørnland, 2015):

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t$$

The formula shows that an AR model is lagged values of itself and includes a coefficient for each lagged value of y. There are several methods to select the optimal number of lags, for instance Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) or a combination of the two. Due to the scope of the thesis, we have chosen to focus on one criterion when selecting lags, namely AIC. AIC is a model selection method, which estimates the quality of each model, relative to the other models. The criterion aims to find a tradeoff between goodness of fit and simplicity of the model (Bjørnland, 2015). The AIC test is performed on several models, and the model with lowest score is considered the best model. BIC punishes the complexity of the models more heavily, which implies that it may include too few lags in the models (Bjørnland, 2015). Thus, we chose to use AIC to avoid underfitting the models.

3.4 Autoregressive distributed lag model

An *autoregressive distributed lag (ADL)* model allows us to include other variables than lagged values of the dependent variable. We can write an ADL model in a general form as (Bjørnland, 2015):

$$y_t = \mu + \sum_{j=1}^{p} \phi_j y_{t-j} + \sum_{k=1}^{K} \sum_{q=1}^{Q_k} \beta_{q,k} x_{t-q,k} + \varepsilon_t$$

The term after the intercept is the autoregressive part. The next term is the distributed lag model. The x's represent other variables than lagged values of the dependent variable and can have several lags as well. Adding these extra variables to the model can help explaining the dependent variable better. The number of optimal lags in this model is determined by AIC, for the same reasons explained in subchapter 3.2.

4. Data

In this section, we will describe which data is collected and how they are categorized. We will also discuss how we transformed the data in order to fit the requirements of common unit scales and stationarity for PCA, as described in subchapter 3.1. An overview over which transformations was conducted for each specific variable, as well as the respective categories, can be found in Appendix 1. Last, we will evaluate the data collected.

4.1 Data collection

We collected 149 variables from Macrobond. The variables were chosen based on perceived relevance to GDP and availability in the sample period. Due to the method, an equal starting point for all the data was necessary. The data was collected from 1995Q1 until the most recent release. The decision was based on the need for a sufficient sample period, combined with a large quantity of variables.

The 148 variables are put into 12 different categories. When we categorized them, the economic content of each variable was considered. These categories are; *All Variables, Employment, Export & Import, Foreign Financials, Government Statistics, Housing, Interest Rates & Swaps, NORLEI, Money & Credit, Norwegian Financials, Other Business Statistics and Production.* The categories are shown in the table below.

Table 2: List of categories and included number of variables

Category	Number of variables
All Variables	148
Employment	11
Export & Import	20
Foreign Financials	11
Government Statistics	15
Housing	16
Interest Rates & Swaps	18
Money & Credit	12
Norwegian Financials	14
Other Business Statistics	13
Production	10
NORLEI	8

Note: The table shows the categories and the number of variables included in each category. See Appendix 1 for full list of variables.

The category All Variables contains all variables listed inn Appendix 1. Employment consists of different variations of unemployment. Interest Rates & Swaps consists of interest rates with different maturities, interest rate spreads and swaps. Further, we have Government Statistics which consists of the most important revenue and expenditure measures, as well as debt for the Norwegian government. Other categories, such as Other Business Statistics, is based upon variables with a bit more variation. The category includes variables with different measurements of bankruptcies, domestic trade and sentiment surveys. Export & Import contains variables regarding export and import of different goods and services.

The category Norwegian Financials contains exchange rates and stock indices for the Norwegian market, as well as the North Sea brent oil price. The variables in Money & Credit measures different interest rates, credit measures and the Norges Bank's balance sheet. The Housing category includes variables such as real estate prices and construction measures. The variables included in the category Production is mainly capacity utilization in industrial production, and further different measures regarding oil and gas, manufacturing and mining and quarrying. The variables included in the category NORLEI are leading economic indicators for the Norwegian economy and is shown in subchapter 5.3.

Further, we have a category based on international measures, which is called Foreign Financials. Norway is a small open economy which is affected by international markets. Therefore, we wanted to analyze whether international measures could forecast Norwegian GDP growth accurately. It is hard to determine what is the best variables for such a category, but variables from the US and Europe seems like a reasonable choice. The reason being that these are the closest trading partners of Norway. The variables include GDP, equity indices, government bonds and government bills from the US and the EU area.

4.2 Data transformation

The data collected are published with different frequencies, e.g. at a daily, monthly or quarterly frequency. In order to compare forecast values with actual observed data, we need the forecasted series to be denoted with the same frequency as the series we are forecasting. Since GDP is published quarterly, we need to transform the variables to quarterly frequency. This was done by taking the end of period value, the sum, or in some instances the average. The frequency transformations for each variable is shown in Appendix 1.

For financials, exchange rates and interest rates we averaged values for each quarter. These variables are released daily and are relatively volatile, thus taking the average made most sense. For real values, the sum was used to transform to quarterly frequency. An example of this are how many dwellings were built, on a monthly basis. To obtain the first quarter value, the sum of January, February and March is calculated, instead of taking the average. This way we get the true number of dwellings built in a quarter. For some variables measured as indices, the end of period value was used. In general, these variables have low volatility, hence we used the end of period value. This is an advantage as we get the most recent value, which is more realistic in terms of forecasting.

Many variables had a clear seasonal pattern, which is typical for many macroeconomic variables. Variables with seasonal patterns have peaks or troughs in the same quarter each year, and this was detected graphically. For instance, household consumption is always higher in the fourth quarter due to holiday shopping, and this needs to be adjusted for. If the seasonal pattern is not considered and adjusted for, there might be biased results in analysis.

There are several methods to seasonal adjust, however we chose to use the Pindyck-Rubinfeld seasonal adjustment method (Pindyck, 1998). We chose this method because it is able to remove the seasonal effect adequately, and do not require external software. This method separates each variable into a trend component, a cyclical component, an irregular component and a seasonal component. The Pindyck-Rubinfeld method allows for exclusion of the seasonal component to get our data seasonal adjusted. The full derivation of Pindyck & Rubinfeld can be viewed in Appendix 3.

A requirement for the PCA method is that the variables are transformed to common unit scale and stationarity, as mentioned in subchapter 3.1 A time-series is stationary if it has a constant mean, constant variance and that $\text{cov}(y_t, y_{t-s}) = \gamma_s$ depends on s, not t (Bjørnland, 2015). To obtain the stationary time-series, the natural was logarithm calculated, except for variables already denoted in percentage rates. For variables denoted in levels, we calculated the first differences in logarithms, which gives the quarterly growth rate. For some variables, the second difference needed to be calculated, which is the difference of the difference. This was done on variables that did not become stationary when first differencing. The Augmented Dickey-Fuller test was used to decide whether a series was stationary or not, as well as analyzing the series graphically. Additionally, the variables are measured in a common unit scale. The variables list with transformations are shown in Appendix 1.

4.3 Data evaluation

The data is collected from Macrobond. Because Macrobond collects data from many different sources, we found it convenient to use their platform. The sources Macrobond have used for the variables is listed in Appendix 1. In Appendix 1, we see that Statistics Norway is the original source for the majority of the data. Statistics Norway is known as a reliable source of data, since the government are responsible for collecting and reporting it. Further, many variables in the dataset are originally published by Norges Bank and Oslo Stock Exchange. The remaining variables are originally published by Central Banks and well-known exchanges. Hence, the validity of the data, i.e. if our data is a good representation of the reality, is expected to be high.

The reliability of the data is measured by how precise they are and how the processing is done in terms of consistency in the results. An issue in our reliability is that some of the variables are revised after their initial release date. For instance, for the Norwegian economy, the final GDP release is August two years after the initial release. For our dataset, this implies that all GDP observations from 2017q1 and onwards is initial releases and will be revised in the future. All observations prior to 2017q1 are final releases and will not be revised further.

If we are to use the method in this thesis to forecast from the present, we need to address the issue of publishing lags. Our method assumes that all data is available instantaneously after the end of each quarter. In practice, many of the variables used are published with a lag, often weeks or months after the end of the respective quarter. This implies that we are not able to forecast instantaneously after the end of the present quarter. This can be solved by a Kalman filter, which estimates the most recent data release (Doz et al., 2012). However, this is beyond the scope of this thesis.

5. Methodology

The methodology chapter discusses what we have done with our data in order to answer the empirical research questions. First, we will explain the forecast method, which is the basis for understanding further computations in the method section. Next, the leading economic index with Norwegian data is created. This index will be used further to forecast GDP growth. Then, we will go through the estimations in the PCA, which is an essential part of the forecast estimations. Further, the forecast models, including the benchmarks, are explained. Last, we will elaborate on how the forecast performances will be evaluated.

5.1 Forecast methodology

In this thesis we will use a forecast method called Pseudo out of sample forecasting (J. Stock & Watson, 2008). This implies using an *in-sample period* and an *out of sample period*, and forecast h-steps ahead. The *in-sample period* is the period where models are estimated and selected as basis for forecasting, while the *out of sample period* is the period used to evaluate the forecast performance. The idea is to forecast *h*-steps, where *h* denotes number of periods to forecast, from the start of the out of sample period denoted by *t*, then re-estimate the models at *t+1* and again forecast h-steps ahead (J. Stock & Watson, 2008). The process is repeated until the end of the out of sample period is reached. This implies that we for each quarter forecast h-periods ahead, where all the observed data prior to each starting quarter of forecast is taken into account.

In the in-sample period we are estimating the PCA, the AR and the ADL models. As mentioned, our data starts in the third quarter of 1995. Thus, this will naturally mark the starting point for the in-sample period. We have chosen to end the in-sample period in the first quarter of 2014. The reason for this has to do with wanting a substantial duration of the in-sample period. If the in-sample period is too short, the forecast would be more unreliable due to less observations of historical data in the models. Thus, a longer in-sample period is preferable.

The out of sample period extends from the second quarter of 2014 to the first quarter of 2018. The period spans to 2018q1 because this is the end point of observed data. The reason for this has to do with seasonal adjustment, which uses a 4-quarter moving average. This implies that we do not have observed seasonal adjusted data on Norwegian GDP after 2018q1, and thus we are not able to calculate the RMSE values.

The table below shows a forecast where h=4, i.e. a forecast of 4-quarters. The light grey shaded area shows the period of model estimation, while the darker shaded grey areas are forecasts. We see that the method works such that we are currently standing in 2014q1, where we estimate the models until and including 2014q1. Further, we forecast 4-quarters ahead starting 2014q2 until 2015q1. Next, we move to the following quarter, and re-estimate the models with new actual observations until and including 2014q2. Then we forecast 4-quarters ahead until 2015q2. This is repeated until the end of the out of sample period, i.e. 2018q1. The method is the same for the 8-quarter and 12-quarter forecast horizons. Doing this, we assume that all data is published in real time, and the model estimations are performed directly after publishing.

Figure 1: Example of 4-quarter pseudo out of sample forecast

In-sample period	t 2014Q1	t+1 2014Q2	t+2 2014Q3	t+3 2014Q4	t+h 2015Q1	t+h+1 2015Q2	t+h+2 2015Q3	t+h+3 2015Q4

Note: The figure shows the Pseudo out of sample 4-quarter forecast horizon method. It works similarly for the 8-quarter and 12-quarter horizon. The light grey shaded area show the period of model estimation, while the darker shaded area show forecast periods. For the first forecast we see that we estimate the models until and including 2014Q1, and then forecast 4-steps. Next, we estimate models until and including 2014Q2, and forecast 4-steps starting 2014Q3. This is repeated until the end of the out of sample period is reached.

It is imperative to mention that the h-step forecast is not based on actual observed values further than the start period of the forecast. If we are to forecast four quarters from period t, the fourth forecast value is only based on model estimations from actual observed data up to period t, and then further based on the previously three periods forecasts in t+1, t+2 and t+3. This gives a realistic forecast of the h-steps. It also implies more uncertainty the longer forecast period. The forecast in t+1 will be more accurate as it is based on actual data from the previous period, while a t+4 forecast will be more uncertain as it is based on three previous forecasted values.

5.2 Principal Component Analysis

In this thesis, we are analyzing which category of variables that forecast Norwegian GDP growth most accurate. Therefore, we are running a separate PCA for each category, before we use the relevant components from each PCA to forecast. This implies that each PCA is run with 10-20 variables, depending on which category is analyzed. In addition, we are also running a PCA with all of the variables in the dataset. This is to see whether a PCA with all of the variables are able to forecast more accurate than the categories.

From the PCA, we obtain, as mentioned in subchapter 3.1, the element of the eigenvector. This element explains the contribution of each variable to each component. From the output of the PCA we can see which of the variables that contributes the most to the components. However, we also see that almost every variable contributes somewhat to the component as well. It may not be high contributions, but the variables still contribute somewhat. This implies that if we run a PCA separately for each category, which is based on economic content, we can state that these types of variables are able to forecast accurately. Conversely, if we run a PCA with all of the variables, the output will not give a clear indication of which category is able to forecast accurately, because the components will capture variances from different types of variables, with different economic content.

When deciding the number of components to use from each category in further estimations, we have decided to use a combination of cumulative proportion and eigenvalues. First, we have set a constraint such that no components with an eigenvalue below one is used in the forecast equations. This is due to that these components will not sufficiently add value to the estimations. Next, we strive to obtain a cumulative proportion of around 60%-70%, i.e. the number of components that captures around 60%-70% of the total variation in the original dataset. We see that this most often is obtained by using two components. The components beyond these values often only captures 2%-5% of the total variation. Thus, we conclude that two to three components explaining 60%-70% is optimal to use in further forecasts. Further, we are focusing on not adding too many components, which could affect the parsimony of the model. This is in line with Koop and Potter (2004), who argues that two components are on average the best choice, in order to create models that have the best predictive power.

When the number of optimal components is chosen for each category, we do not update the number of components in consecutive periods. This is because the proportions of the components are changing insignificantly when adding extra information only from some years. However, the chosen components are updated with new information each period t. This implies that we first run a PCA on the relevant category and choose the number of optimal components. Next, we run a PCA for each period t, such that the chosen components are updated with information up to and including period t. This is done for each h-step forecast for every period t.

In the table below we see each category and the results from their respective PCAs, for the in-sample period of 1995q3 to 2014q1. The numbers in the rows Component 1 – Component 3 explains how much of the variation variables from the respective category that is captured by the component. The total variation captured explains the total variation from the components that we have chosen to use in further estimations. For instance, for the Employment category we are using two components which captures 62% of the total variance from the variables in the category Employment. For the Government category, we have chosen to use three components when forecasting, which captures 59% of the total variation from the variables.

Table 3: Percentage of variation explained by principal components

Categories	Number of variables	Component 1	Component 2	Component 3	Total variation captured
All Variables (Tot. 6 PCs)	140	0.14	0.08	0.07	~ 0.44
Employment	11	0.42	0.20	-	0.62
Export & import	20	0.25	0.12	0.11	0.48
Foreign Financials	15	0.54	0.13	-	0.67
Government Statistics	16	0.28	0.19	0.12	0.59
Housing	18	0.47	0.18	-	0.65
Interest Rates & Swaps	12	0.38	0.28	-	0.66
Money & Credit	14	0.21	0.18	0.15	0.55
Norwegian Financials	11	0.49	0.21	-	0.70
Other Busines Statistics	13	0.29	0.22	0.12	0.63
Production	10	0.29	0.19	0.13	0.61

Note: Table shows the PCA analysis for each category for the in sample period of 1995q3 until and including 2014q1. Number of variables explains the total number of variables included in each category. Number below Component 1 - 3 explains the variance captured of the total variance from the respective category, by the respective component. Total variance captured explains the total variance captured by the components used in further estimations. For instance, when forecasting using the category Production, we will forecast using 3 components capturing 61% of the total variance from the Production variables. Special case: For the All Variables category, we are using 6 components in forecasting, capturing 44% of the total variance from all variables.

From the table we see that most of the categories is well explained by only two or three components. However, we see two outliers in the total variance captured in Export & Import, and the All Variables category. For Export & Import, we chose to use three components, as the fourth component captured very little of the total variation. If we were to increase the total variation captured to 60%, several components would have had to be included. For the All Variables category, which includes 140 variables, we are using six components in further estimations. These components captures 44% of the total variation. In general, we aimed to cut off at three components for all categories. However, for the All Variables category we wanted to add more components in order to capture a significant amount of total variation.

5.3 Norwegian Leading Economic Index

In this part, we replicate The Conference Board Leading Economic Index (LEI) with Norwegian data. The methodology used to create the *Norwegian Leading Economic Index*, hereby *NORLEI*, is based on the same approach as LEI, explained in Appendix 4. For NORLEI, we will forecast using this index, and not construct components from PCA. The leading index with Norwegian data is created with a starting point in the third quarter of 1995.

The index consists of the variables shown in the table below. We see that the largest contributors to change in the NORLEI index is the Credit index and Consumer expectations. New orders and the Yield spread also contributes significantly. Building permits, Hours worked, OSEBX and Index of industrial production contributes less to changes in NORLEI.

Table 4: Variables included in NORLEI and standardization factors

NORLEI	**Standardization factors**
Productivity, Hours Worked, Employees	0.044
Index of Industrial Production	0.047
Credit Index (Swap spread, NIBOR spread)	0.335
OSEBX	0.014
Yield Spread (NO 10 year gov.bond less 3 month gov. bill)	0.129
New Orders	0.145
Bulding Permits, New Dwellings	0.010
Consumer Expectations	0.275
Sum	1

Note: The table shows the variables included in the NORLEI index. Further, it shows the standardization factors, which explains each vaiable's quarterly contribution to the NORLEI index.

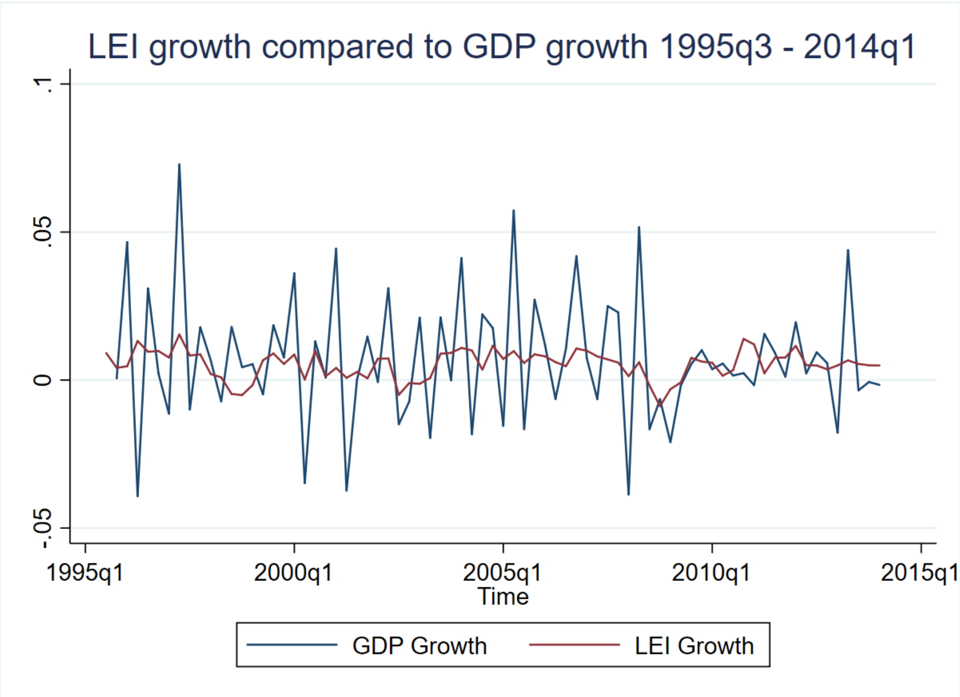
The NORLEI is calculated using the method of The Conference LEI, which is shown in Appendix 4. We have computed the quarter-to-quarter change for the variables Index of Industrial Production, OSEBX and Dwellings. For the Yield Spread and the Credit Index we will use the quarterly level in further calculations. The Credit Index consists of two spreads, NIBOR 3-month less 3-month government bill, and 2-year swap rate less 2-year government bond. New Orders and Consumer Expectations are diffusion indices. These are normalized by subtracting the mean and dividing by the standard deviation.

Next, the standard deviation is calculated for the variables, and then the results are inverted. By standardizing the inverted volatilities such that they sum to one, we obtain the standardization factors. This is the quarterly contribution for each variable. Each variable’s adjusted quarterly contribution is calculated by multiplying each observation for each variable with its associated standardization factor. Summing these contributions for each quarter, obtains the growth rate for the index.

The fourth, fifth and sixth step explained in Appendix 4 is not relevant to NORLEI. The fourth step of creating an adjustment factor is not possible, as we are not creating a coincident index. The fifth step, calculating the index in levels is not relevant, as we want the index denoted in growth rate in order to forecast GDP growth. Since percentages are used, there is no need to rebase to 100, which is the sixth step.

The graph below is an indicator that NORLEI is coincident, as it seems to correlate with GDP growth. Further, the NORLEI is less volatile than the GDP growth. Most peaks and troughs also suggest that NORLEI is coincident.

Figure 2: LEI Growth compared to GDP Growth 1995q3 - 2014q1



As mentioned, the purpose of the LEI is to predict directions of the general economy. This implies that the index in theory should be leading to GDP. The table below shows that the NORLEI is not leading, but rather coincident. With zero lags, NORLEI and GDP growth has a correlation of 0.58. The correlation for lags and leads are around 0.10 and 0.19 for two period lead, which further is an indicator that NORLEI is coincident.

Table 5: Coefficient of correlation between GDP growth and NORLEI

	Coefficient of correlation between GDP growth and NORLEI						
	Quarterly leads and lags						
	-3	-2	-1	0	+1	+2	+3
NORLEI	0.09	0.11	-0.13	0.58	-0.08	0.19	0.06

Note: Table shows the coefficient of correlation between the GDP growth and the NORLEI index, in the period 1995q3 to 2018q1. 0 implies that there are no leads and no lags. -3 is the correlation when NORLEI is leading GDP with 3-quarters.+3 is the correlation when NORLEI is lagging GDP with 3-quarters

These results indicate that a replication of the Conference Board LEI does not translate well for the Norwegian economy. One reason for this can be that leading indicators for the US economy does not translate as leading indicators for the Norwegian economy. Although the NORLEI performs weak as a leading indicator, it does not disregard the index as a forecasting model.

5.4 Benchmark models

5.4.1 Autoregressive model

When creating the benchmark forecasting model of the autoregressive (AR) model, the number of lags needs to be determined. For the AR benchmark model, the number of lags is chosen based on AIC, as mentioned in subchapter 3.2. When analyzing the models with AIC, we found that the model will include two lags for all forecast horizons, for all periods. This implies that we obtain an AR(2) model for all periods. Hence, in the AR model we make a forecast based on the previous value of GDP growth for the two last periods to predict future GDP growth.

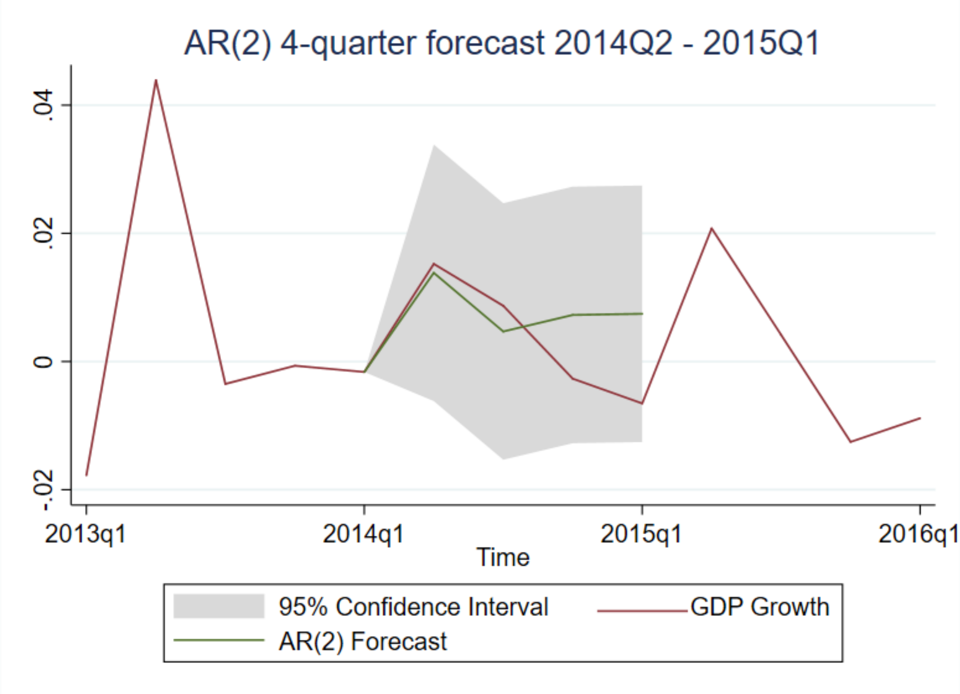
When using this as a benchmark, up to and including time t is the model estimation period. This is done for all the out of sample forecasting periods. Hence, the benchmark model will change each time we increase t, as all values up to and including time t will be used to estimate the benchmark model. As mentioned, the number of lags will not change, only the coefficients.

The formula below shows that our benchmark forecast model is based on forecasted values of lagged GDP growth. The formula is the general formula of an AR(2) process, which is used for all forecast horizons, for all periods. h represents the number of periods forecasted, i.e. 4-, 8- or 12-quarters. t is the starting point of the forecast, where the general AR model in sample is estimated up to and including. |t denotes that the model is estimated up to and including t.

$$y_{t+h|t} = \mu + \phi \hat{y}_{t+h-1} + \phi \hat{y}_{t+h-2} + \varepsilon_{t+h}$$

In the graph below, we see an example of a forecast for the period 2014Q2-2015Q1 with a 95% confidence interval. The AR(2) model is able to perform an accurate forecast for the first period. The reason is that actual values are being used. The forecast in 2014Q4 starting in period 2015Q1 is using the predicted values of 2014Q3 and 2014Q2 which deviate from the true GDP growth. This implies that a forecasted value in period 2014q4 is more inaccurate than a forecasted value in 2014q2.

Figure 3: AR(2) 4-quarter forecast 2014Q2 - 2015Q1



5.4.2 Random walk

A random walk model is defined as a process where the current value is based on the sum of the previous value and an error term. The error term is assumed to be identically and independently distributed. This is shown in the formula below (Chan, 2011).

$$y_t - y_{t-1} = \varepsilon_t \text{ , when rearranged: } y_t = y_{t-1} + \varepsilon_t$$

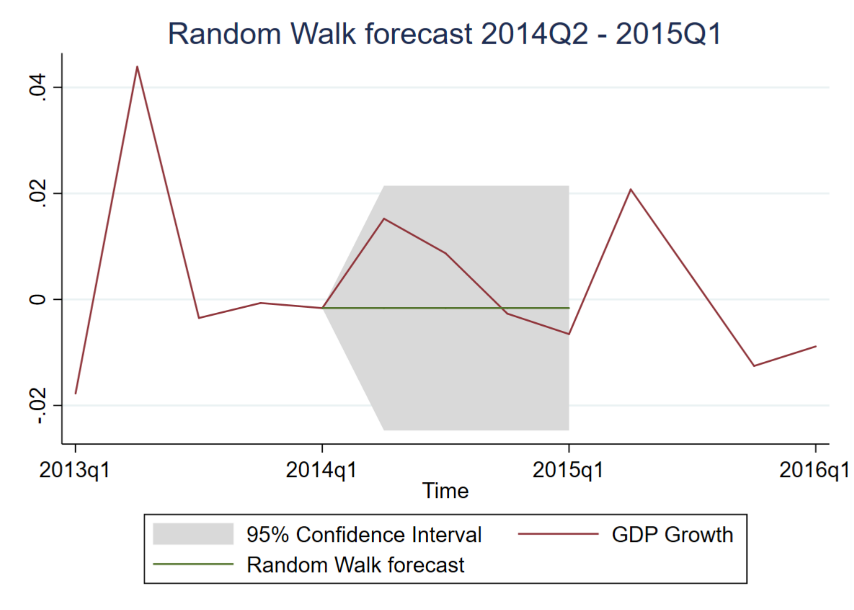
Forecasting based on this series gives us a random walk forecast and it is defined as a model where the forecast value is the same as the previous value. The reason for this is that the model is a stationary series which are equally likely to increase or decrease. A random walk forecast performs surprisingly well over time when forecasting a stationary series (Chan, 2011). An h-step forecast of random walk is given by:

$$y_{t+h|t} = y_t$$

Which is the model we use as benchmark. This model is updated with constant growth each time we increase t.

The graph below shows an example of a random walk forecast for the period 2014Q2 to 2015Q1 with a 95% confidence interval. We see the random walk forecast uses the last actual value of GDP growth to forecast for the entire period. Therefore, when we forecast the period 2014Q2-2015Q1 we use the value of 2014Q1 as forecast for the entire period. In this case, a 4-quarter forecast is shown, but the same method is used for 8- and 12-quarter forecasts.

Figure 4: Random walk forecast 2014Q2 - 2015Q1



5.5 Autoregressive distributed lag models

To calculate the ADL models, we need to decide how many lags to use for each term of the equation, which is done by AIC. Below we see the general form of a forecast ADL model (Bjørnland, 2015). The model consists of a constant term followed by the sum of the lagged values of GDP growth. Further, the model includes the sum of lagged components, where the number components is denoted by n. The number of lags is denoted by *i* for the values of GDP growth, and *l* for component n.

$$y_{t+h|t} = \mu + \phi\Sigma y_{t+h-i} + \sum \beta_n \Sigma PC^n_{t+h-l} + \varepsilon_t$$

The number of components and lags differ from each model. Below, we see an example of the forecast model for the Norwegian Financials category. The category has two lags of GDP growth, three lags of component 1 and three lags of component 2.

$$y_{t+h|t} = \mu + \phi y_{t+h-1} + \phi y_{t+h-2} + \beta_1 FIN^1_{t+h-1} + \beta_1 FIN^1_{t+h-2} + \beta_1 FIN^1_{t+h-3} + \beta_2 FIN^2_{t+h-1} + \beta_2 FIN^2_{t+h-2} + \beta_2 FIN^2_{t+h-3} + \varepsilon_t$$

The table below shows each category and the model specification for the respective categories. The lag lengths are decided by AIC, as mentioned earlier. The models are updated each forecast period t, for each h-step forecast horizon. This implies that the lags can change for each period t. However, this is not the case. Running the different models and testing with AIC, show that the optimal lag lengths do not change when re-estimating in period t+1 until period t+n. Thus, the lag lengths in the table is valid for all periods t, for all forecast horizons.

Table 6: Forecast model specifications

		Optimal number of lags						
Category	**Model type**	**AR**	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**
AR Benchmark	AR	2	-	-	-	-	-	-
All Variables	ADL	2	4	3	2	4	2	4
Employment	ADL	2	2	2	-	-	-	-
Export & Import	ADL	2	2	2	2	-	-	-
Foreign Financials	ADL	2	2	1	-	-	-	-
Government Statistics	ADL	2	2	1	1	-	-	-
Housing	ADL	2	2	1	-	-	-	-
Interest Rates & Swaps	ADL	2	2	2	-	-	-	-
Money & Credit	ADL	2	1	1	2	-	-	-
Norwegian Financials	ADL	2	3	3	-	-	-	-
Other Business Statistics	ADL	2	2	3	1	-	-	-
Production	ADL	2	2	2	1	-	-	-
Category	**Model type**	**AR**		**NORLEI**				
NORLEI	ADL	2		2				

Note: The table shows the model specification for each category in forecasting. For the model types, AR denotes an Autoregressive model, while ADL denotes an Autoregressive distributed lag model. The columns AR - C6 denotes the number of lags for the respective parts of the models. AR denotes the lags for the Autoregressive term, while C1-C6 denotes the number of lags used for Component 1 to Component 6. The NORLEI is not forecasted using PCA, but with an ADL consisting of an AR term and the growth of the index. The column NORLEI denotes the number of lags for the growth of the NORLEI, in the forecast model.

As mentioned, each model consists of the benchmark as basis. This implies that the number in the column “AR” denotes optimal lag length of GDP growth. The columns C1 – C6 denotes the optimal lag length of component 1 to component 6 for each category, respectively. For instance, for Other Business Statistics, we have a model consisting of two lags for the AR part, two lags for component 1, three lags for component 2, and one lag for component 3. This is also the case for all the categories, except the NORLEI. The NORLEI is not modelled with PCA, and thus the number in the column "NORLEI" denotes the number of optimal lags for the growth of the NORLEI.

5.6 Forecast performance evaluation

The forecast performances will be evaluated by the usage of the *root mean square error (RMSE)*. RMSE squares the errors before averaging, and thus gives relatively high weights to large errors. In forecasting, it is undesirable to obtain large errors. Hence, RMSE is a good metric to evaluate forecast performance. An RMSE value of zero indicates a perfect fit, and the goal of the forecasts is to minimize the RMSE. For evaluating each forecast period, we will use the RMSE, which is defined as (Bjørnland, 2015):

$$RMSE = \sqrt{\frac{\sum(y - \hat{y})^2}{n}}$$

Where y is the actual observed GDP growth, and $\hat{y}$ is predicted values of y. n is the number of periods. Using this method, we will obtain several RMSE values for each category in each h-step forecast method. For instance, forecasting 4-steps, we will obtain 12 RMSE values for each category, given an out of sample period of 2014Q2 – 2018Q1. Due to the large number of RMSE values, we average the RMSE values for each category for each h-steps forecast series.

In addition, we will use the relative mean squared error (relative MSE), which is relative to the AR benchmark model. This implies that a relative MSE of one is equivalent to performing the same as the AR benchmark. A relative MSE value below one implies an outperformance of the benchmark.

While RMSE is a more accurate measure of performance, it can be hard to interpret. The interpretation becomes more extensive for the RMSE due to squared errors, which implies that it weighs outliers in the error higher. However, this is not the case for MAE, which weighs all the errors the same. The MAE is more intuitive in the sense that it can be explained as a mean deviation in the forecast from the real observed values. MAE explains the absolute average distance between the two series, and is given by the sum of the absolute value of GDP growth minus predicted values of GDP growth, divided by number of periods (Chan, 2011):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|(y_i - \hat{y}_i)|$$

6. Forecast results

This chapter presents the forecast results from each forecast horizon. This will be done in terms of presenting the average RMSE and the relative MSE values. We will split up the results based on each forecast horizon and present these results separately. The results will be discussed and analyzed in chapter 7.

6.1 4-quarter forecast horizon

We will start with the 4-quarter forecast horizon. The table below shows the forecast results from each category in terms of average RMSE, including the AR benchmark and the Random walk model. All the categories, except NORLEI, is forecasted using components from the PCA. The average RMSE explains, as mentioned, the average of the twelve RMSE's calculated from each forecast. The column of "Min" shows the lowest RMSE values, while the "Max" column shows the maximum value of the RMSE's for the respective categories. These values are included to show how much the performance of the forecasts vary across different forecast periods. The full table of all the RMSE values before averaging, is shown in Appendix 2.

Table 7: Average RMSE for 4-quarter forecast horizon

Categories	Rel. MSE	Avg. RMSE	Min	Max
AR Benchmark	1.00	0.019	0.010	0.031
Random Walk	2.00	0.027	0.012	0.057
All Variables	0.48	0.013	0.008	0.020
Employment	0.67	0.016	0.010	0.026
Export & Import	1.14	0.021	0.010	0.038
Foreign Financials	1.21	0.021	0.010	0.038
Government Statistics	1.84	0.026	0.008	0.041
Housing	1.05	0.020	0.012	0.034
Interest Rates & Swaps	0.94	0.019	0.010	0.033
Money & Credit	0.95	0.019	0.008	0.027
Norwegian Financials	1.03	0.020	0.011	0.035
Other Business Statistics	0.93	0.018	0.007	0.029
Production	0.47	0.013	0.007	0.020
NORLEI	1.09	0.020	0.009	0.034

Note: The table shows the 4-quarter forecast performance for the benchmarks and the categories using pseudo out of sample forecating. The forecast period is 2014q2 to 2018q1. All categories, except NORLEI and benchmarks, are estimated using PCA. NORLEI is estimated using method from Conference Board, explained in chapter 5.2. Method for estimating benchmarks are explained in chapters 5.4.1. and 5.4.2. The Rel.MSE explains the MSE value of each category relative to the AR benchmark. Avg. RMSE explains the average RMSE value of all forecasts done with 4-quarter horizon for the respective categories, i.e. 13 forecasts per category. Min and Max explains the minimum and maximum RMSE values of these 13 forecasts.

We see that the categories Random walk, Export & Import, Foreign Financials, Government Statistics and Norwegian Financials, have a minimum value of around 0.010, and maximum values above 0.035. These are also the categories with the highest average RMSE values, i.e. the categories that forecasts the least accurate. In general, we see that the forecasts are similar when it comes to minimum, but the maximum values are more volatile.

Furthermore, there is a pattern in the RMSE values for the different forecast periods, which can be seen in Appendix 2. The pattern shows that most of the categories forecast quite well in the first five periods. For the forecasts with a starting point between 2015q2 and 2016q1, all the RMSE values suddenly rises. Most of the values increases by around 0.012, which is double the past values. This is explained by the GDP growth, which suddenly becomes more volatile in this period. When the GDP growth is more volatile, it becomes harder to forecast well. Conversely, when the GDP growth is less volatile, as it is from 2014q1 to 2015q1, the forecasts are significantly better. In the periods where GDP growth is more volatile, the categories Employment, Production and All Variables forecast more accurate than the other categories.

We see that the RMSE for the AR benchmark is 0.019, with a relative MSE of 1.00, which is because the benchmark is the basis for comparison. There are three categories that performs significantly better than the others compared to the AR benchmark. This is the All variables category with a relative MSE of 0.48, Employment with 0.67, and Production with 0.47. A relative MSE of 0.47 implies an outperformance of the AR benchmark by 53%. This is also the best performer with 4-quarters forecast horizon.

Moreover, we see that there are some categories that slightly outperforms the AR benchmark. This is the categories Interest Rates & Swaps, Money & Credit and Other Business Statistics. NORLEI is slightly outperformed by the AR-benchmark, with a relative MSE of 1.09. On the other hand, we see that the categories that performs the least accurate are Random walk, Government Statistics and Foreign Financials. These are quite extensively outperformed by the AR benchmark, and does not forecast GDP growth accurately at a 4-quarter horizon.

6.2 8-quarter forecast horizon

The table below shows the results from the 8-quarter forecast horizon. The starting point is 2014q1 and the last forecast has a starting point of 2016q2, which gives a total of nine forecasts for each category. Comparing the benchmarks, we see that the AR benchmark outperforms the Random walk model. The AR benchmark has an average RMSE of 0.021 compared to the Random walk which has 0.024. They both have the same minimum value of RMSE. However, the table show that the Random walk has a higher maximum value of

RMSE. This is also reflected in the table, where the relative MSE is 1.3 for the Random walk model.

Table 8: Average RMSE for 8-quarter forecast horizon

Categories	Rel. MSE	Avg. RMSE	Min	Max
AR benchmark	1.00	0.021	0.013	0.025
Random walk	1.30	0.024	0.013	0.031
All variables	0.55	0.015	0.011	0.018
Employment	0.70	0.017	0.012	0.020
Export & Import	1.43	0.025	0.014	0.031
Foreign Financials	1.44	0.025	0.012	0.031
Government Statistics	2.13	0.030	0.013	0.044
Housing	1.04	0.021	0.014	0.027
Interest Rates & Swaps	1.01	0.021	0.013	0.026
Money & Credit	1.16	0.020	0.012	0.025
Norwegian Financials	1.23	0.023	0.013	0.027
Other Business Statistics	1.05	0.021	0.009	0.028
Production	0.38	0.013	0.007	0.016
NORLEI	1.37	0.024	0.011	0.031

Note: The table shows the 8-quarter forecast performance for the benchmarks and the categories using pseudo out of sample forecating. The forecast period is 2014q2 to 2018q1. All categories, except NORLEI and benchmarks, are estimated using PCA. NORLEI is estimated using method from Conference Board, explained in chapter 5.2. Method for estimating benchmarks are explained in chapters 5.4.1. and 5.4.2. The Rel.MSE explains the MSE value of each category relative to the AR benchmark. Avg. RMSE explains the average RMSE value of all forecasts done with 8-quarter horizon for the respective categories, i.e. 9 forecasts per category. Min and Max explains the minimum and maximum RMSE values of these 9 forecasts.

The production category is the most accurate performer with an average RMSE of 0.013. Furthermore, the relative RMSE compared to the AR benchmark is 0.38. Both measures are considered to be accurate forecast performances. The minimum value of RMSE is 0.007 for the Production category, which is the lowest value for all categories. In Appendix 2 we see that the forecast starting in 2014q2 is also accurate, however the RMSE increases slightly for the next three periods. In the three forecast periods starting 2015q2, 2015q3 and 2015q4, the RMSE values are higher. However, there is a slight decrease in the last period.

The Employment category and the All Variables category also clearly outperforms the AR benchmark. They have similar results regarding the average RMSE, where the Employment category have an average RMSE of 0.017 and the All Variables category model have an average RMSE of 0.015. The minimum and maximum values for the two variables are close to the average, hence the fluctuations are small. The All variable model has a relative MSE of 0.55 and the Employment model 0.70. This shows that both models outperform the AR benchmark with a good margin.

The categories Housing, Interest Rates & Swaps, Money & Credit, Norwegian Financials and Other Business Statistics are all close to the benchmark regarding the average RMSE. This is also reflected in the relative MSE, where none of the categories deviates with more than 0.23. Moreover, Interest Rates & Swaps, Housing and Other Business Statistics deviates less than 0.05.

The least accurate performing categories are NORLEI, Export & Import, Foreign Financials and Government Statistics. They all have an average RMSE above 0.024 and are the only categories in the 8-quarter forecast horizon that is beaten by the Random walk model. In the relative MSE column, we see that Government Statistics has the least accurate performance with a relative MSE at 2.13. NORLEI, Export & Import and Foreign Financials also has inaccurate performances with respectively 1.37, 1.43 and 1.44 as their relative MSE relative to the AR benchmark. The maximum column shows that Government Statistics has the single least accurate forecast, with an RMSE of 0.044.

6.3 12-quarter forecast horizon

Last, we will present the results from the 12-quarter forecast horizon. In the table below, we see the two benchmarks, AR and Random walk, are much closer in their average RMSE than earlier. The AR benchmark still outperforms the Random walk model, by average RMSE of 0.001. The minimum values for the AR benchmark and the Random walk model respectively are 0.018 and 0.019, and the maximum values are 0.021 and 0.024.

Table 9: Average RMSE for 12-quarter forecast horizon

Categories	Rel. MSE	Avg. RMSE	Min	Max
AR Benchmark	1.00	0.020	0.018	0.021
Random Walk	1.19	0.021	0.019	0.024
All Variables	0.61	0.015	0.014	0.017
Employment	0.71	0.017	0.016	0.017
Export & Import	1.55	0.024	0.022	0.026
Foreign Financials	1.38	0.023	0.018	0.025
Government Statistics	2.57	0.031	0.023	0.035
Housing	1.04	0.020	0.018	0.021
Interest Rates & Swaps	0.99	0.020	0.018	0.020
Money & Credit	0.99	0.020	0.017	0.020
Norwegian Financials	1.24	0.022	0.020	0.023
Other Business Statistics	1.22	0.022	0.017	0.023
Production	0.43	0.013	0.011	0.014
NORLEI	1.42	0.023	0.020	0.024

Note: The table shows the 12-quarter forecast performance for the benchmarks and the categories using pseudo out of sample forecating. The forecast period is 2014q2 to 2018q1. All categories, except NORLEI and benchmarks, are estimated using PCA. NORLEI is estimated using method from Conference Board, explained in chapter 5.2. Method for estimating benchmarks are explained in chapters 5.4.1. and 5.4.2. The Rel.MSE explains the MSE value of each category relative to the AR benchmark. Avg. RMSE explains the average RMSE value of all forecasts done with 12-quarter horizon for the respective categories, i.e. 5 forecasts per category. Min and Max explains the minimum and maximum RMSE values of these 5 forecasts.

The table shows that three categories performs accurate compared to the AR benchmark. These three categories are All Variables, Employment and Production. An interesting finding is that the Employment category has a minimum value of 0.016 and a maximum value of 0.017, which makes it a consistently accurate predictor of GDP growth. The Production and the All Variables categories also have small deviations from the average RMSE, but somewhat larger than the employment category.

In the table, we see three categories that are close to the AR benchmark, namely the Housing, Interest Rates & Swaps and Money & Credit categories. Interest Rates & Swaps and Money & Credit have a relative MSE of 0.99, barely beating the AR benchmark. Moreover, the Housing category has a relative MSE of 1.04, which makes it a somewhat less accurate predictor than the AR benchmark. The categories have an average RMSE of 0.020, and their maximum and minimum values do not deviate considerably from this average.

For the 12-quarter forecast horizon, six categories performs inaccurate. None of these categories outperforms the Random walk model, which has a relative MSE of 1.19. The Government Statistics category performs least accurate, with a relative MSE of 2.57. The second least accurate performer is the Export & Import category with a relative MSE of 1.55. Foreign Financials, Norwegian Financials, NORLEI and Other Business Statistics performs similar, but less accurate than the Random walk model.

7. Analysis

In this section, we will analyze the presented results in chapter 6. This will be done in terms of answering the empirical research questions.

7.1 Analysis of forecast results

The predictive power of the models is similar for the different forecasting horizons. All categories stay constant or has a slight increase in average RMSE when increasing the forecast horizon, as shown in chapter 6. When forecasting with longer horizons, the models will have more periods where the estimates is based on previous forecasted values. Thus, the uncertainty increases, and the accuracy of the forecasts decreases. The only exception to this is the Random walk benchmark, which perform more accurate for a longer forecast horizon. The forecast value of the Random walk is only based on the last actual observed value of GDP growth, and thus it does not change. This implies that the uncertainty of the model is not dependent on time, which it is for the other models.

The most accurate forecast performer is the Production category. This category outperforms all other categories and benchmarks for all horizons. It has an average RMSE of 0.013 for all forecast horizons, which is accurate compared to the performance of the other categories. The accurate performance of Production is also reflected in the relative MSE, where it outperforms the AR benchmark for all forecast horizons. For the forecast horizons h=4, h=8 and h=12 it has a relative MSE of respectively 0.47, 0.38 and 0.43. These findings are similar to that of Aastveit and Trovik (2012), who found that using industrial production measures in the dynamic factor model, performs accurate in forecasting Norwegian GDP at a 4-quarter horizon.

The Production category includes variables such as oil supply, capacity utilizations in industry, manufacturing measures and import prices. Norway is a large producer of oil, and thus the oil supply will affect the level of GDP. Further, GDP represents total value of services and products produced in Norway. Thus, production measures will affect the GDP directly. These mentioned factors may be the reason for why the Production category forecasts Norwegian GDP growth accurately.

The All Variables category is the second most accurate performer across all three forecast horizons. The category has an average RMSE of 0.013, 0.015 and 0.015 for forecast horizon h=4, h=8 and h=12. This is similar to the results of Stock and Watson (1999), which showed that an PCA with all of the variables performed well in forecasting inflation. The results from the All Variables category performs slightly less accurate than the Production category. This is an interesting finding in terms of the number of variables in the models. The All Variables category contains 148 variables, while the Production category contains 10 variables. This implies that adding many variables in the PCA and in the forecast models does not necessarily improve the results in terms of forecast accuracy.

The third most accurate performer is the Employment category, based on average RMSE values. The average RMSE values for h=4 is 0.016, for h=8 is 0.017 and for h=12 is 0.017. The Employment category includes different versions of unemployment and statistics regarding labor force. These variables are used as proxies for GDP. This is because if the employment measures are high, there will be a higher amount of services and products produced, which will increase GDP growth. This could explain why the Employment category forecasts accurately.

The NORLEI category is the only category where we do not use the PCA method to forecast. Compared to the AR benchmark it performs less accurate. Its most accurate performance based on the relative MSE measure is 1.09 for the 4-quarter forecast horizon. This implies that NORLEI is not able to outperform the AR benchmark for any of the forecast horizons. Furthermore, the best performance of average RMSE for NORLEI is 0.020 for the 4-quarter forecast horizon. To conclude, the NORLEI constructed in this thesis forecasts Norwegian GDP growth inaccurate.

From the results, we can conclude that using the PCA method to forecast gives mixed results. However, three of our forecast categories were able to achieve more accurate predictions than the AR benchmark model for all forecast horizons. The forecast results show that we are able to obtain forecasts that are more accurate by creating categories, than forecasting using all the variables.

Reviewing all our forecast models, the results show that the Production category is the most accurate predictor of GDP growth. It outperforms the rest of the categories for all horizons, in most cases by a large margin. The Production category achieves an average RMSE of 0.013 for all horizons. The relative MSE indicates that the 8-quarter forecast for the Production category performs better than the horizons of 4- and 12-quarters.

7.2 Analysis of the Production category

In this section, we will analyze the results of the Production category more thoroughly. This will be done in terms of calculating MAE and graphing the best results.

Below, we see the graphs with 95% confidence intervals from the forecasts of the benchmark AR model and the Production category with 8-quarter horizon from 2014q2 and from 2016q2. In the 8-quarter forecast, there are in total nine forecasts. However, we are only showing two forecasts from the 8-quarter forecast horizon period, in order to obtain clean graphs.

Figure 5: Production 8-quarters forecasts from 2014Q2 and 2016Q2

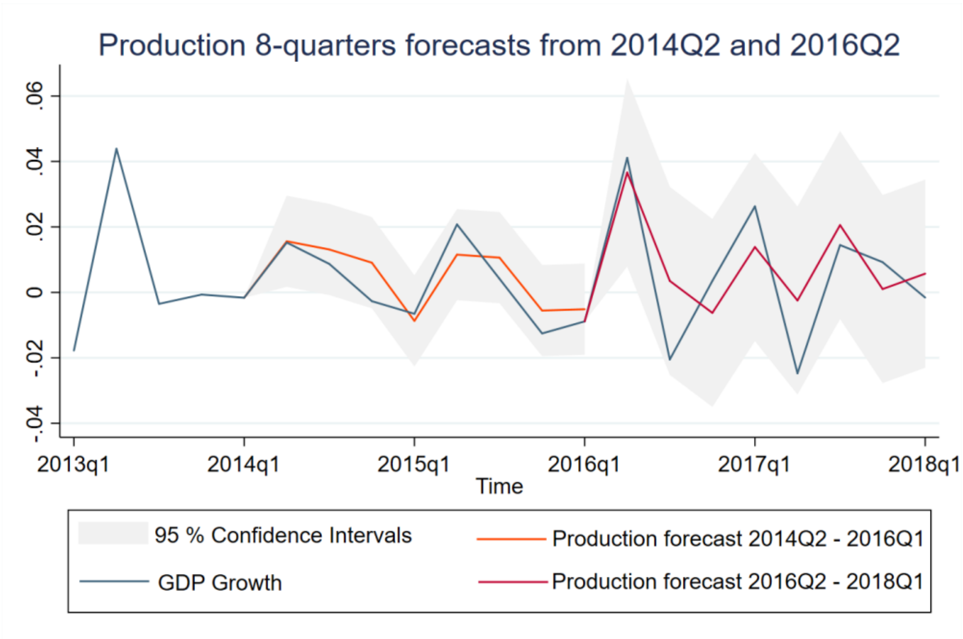
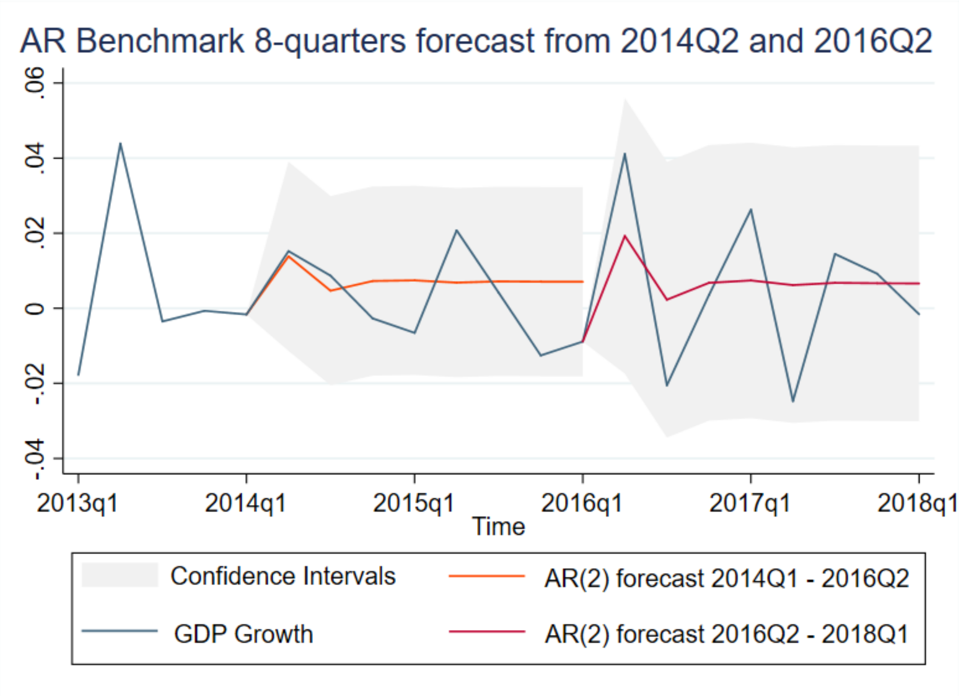


Figure 6: AR benchmark 8-quarters forecasts from 2014Q2 and 2016Q2



The graphs clearly show that the Production forecast outperforms the benchmark AR forecast. The AR forecast quickly revert to the mean, while the Production forecast is able to follow turning points more closely. The Production forecast graph shows that the forecast is more uncertain the longer we forecast, as it deviates more from GDP growth after more forecast steps. Further, we see that the forecast is more accurate when there is less volatility in the GDP growth.

Below, the MAE for the category Production and the AR benchmark, is shown. The MAE is useful to interpret the deviation of the predicted GDP growth, compared to actual observed GDP growth. The average MAE is the average of the MAE's for each forecast-horizon. Furthermore, the values in the table can be interpreted as percentage deviation, as GDP growth is denoted in percentage.

Table 10: Average MAE values for Production and AR benchmark

Forecast horizon	Production	AR model
4-quarter forecast	0.0102	0.0146
8-quarter forecast	0.0102	0.0165
12-quarter forecast	0.0102	0.0156

Note: The table show a comparison of the average MAE of Production and the AR model for the three forecast horizons.

The table shows that the predicted GDP growth by Production, on average deviate with 1%. This is accurate compared to the AR model which deviates with 1.5%, 1.7% and 1.6% for respectively 4-quarter, 8-quarter and 12-quarter forecasts. The Norwegian economy is stable and in periods without a recession one would expect accurate predictions. For a 12-quarter forecast, a 1% deviation on average should be considered to be an accurate prediction. On a 4-quarter horizon, the model might be considered weaker because it is expected to be more accurate for a shorter forecast horizon.

7.3 Potential extensions

In this thesis, we chose to use a cut-off point when selecting how many components to use from the PCA in the forecasting models, explained in subchapter 3.1. However, other combinations of components could have given more accurate forecasts. Thus, an interesting extension could be to run a sensitivity analysis when deciding the number of components in terms of forecast accuracy.

Further, one could research the possibility to combine models based on the results from the PCA. This implies creating forecast models based on combinations of the components that forecasts most accurately from the different categories. Moreover, instead of categorizing the variables based on economic content, the variables could be categorized based on predictive power. This implies forecasting with the variables separately, and then categorizing based on the best performing variables.

NORLEI was based on a replication of The Conference Board LEI for the US. Economy. We found that the NORLEI index were not leading the Norwegian economy, thus one could further investigate this part of the thesis. A possible future research could be to analyze each of the 148 variables selected in the thesis, to see whether these are leading. Further, one could construct an index based on the variables that were found to be leading. Moreover, it would be interesting to research the possibility of creating a real time update of the index, were the index is updated consecutively as they are released.

8. Conclusion

The purpose of the thesis was to analyze whether a dataset containing many variables could forecast Norwegian GDP growth accurately. Further, we wanted to analyze which categorized group that made the most accurate forecast. The first two research questions were answered by using the method of Principal Component Analysis, which compresses large datasets into components that are uncorrelated. Finally, we wanted to analyze whether an index of leading indicators could forecast Norwegian GDP growth accurate. The index of leading indicators for the Norwegian economy (NORLEI) were created as a replication of The Conference Board LEI. The forecasts were made using Pseudo out of sample forecast method. The forecast period was 2014q2 to 2018q1, and the forecast horizons were 4-quarters, 8-quarters 12-quarters.

We found that Principal Component Analysis is able to produce accurate forecasts. The categories Production, Employment, and the All Variable categories forecasts accurate, both in terms of the relative MSE and the RMSE, for all horizons compared to the AR benchmark.

The results show that the Production category outperforms the other categories, both in terms of RMSE and relative MSE. The relative MSE's for Production, were 0.47 for the 4-quarter horizon, 0.38 for 8-quarters and 0.43 for the 12-quarter horizon. This implies that the Production category forecasts accurate compared to the AR benchmark in the period 2014q2 to 2018q1, with the mentioned forecast horizons.

Production is often used as a proxy for GDP, and many Production measures affects GDP directly. This may be the reason for why Production forecasts accurately. In terms of MAE, we see that the forecasts from the Production category on average are deviating 1% from the actual observed data of GDP growth, for all forecast horizons. We can state that this is an accurate performance, especially on a forecast horizon of 12-quarters, as longer forecast horizons are harder to forecast.

The All Variable category is the second best performer in terms of accuracy. The relative MSE's is 0.48 for the 4-quarter horizon, 0.55 for the 8-quarter horizon, and 0.61 for the 12-quarter forecast horizon. The results show that using all variables in PCA and forecasting with the selected components, produces accurate forecasts. However, we see that the All Variables category is outperformed by the Production category. Thus, adding 148 variables in the PCA does not give the most accurate forecast results in the forecast period 2014q2 to 2018q1.

The Norwegian Leading Economic Index was created as a replication of The Conference Board LEI for the US economy. It was created as an index based on Norwegian data, and the growth of the index was used in the forecast models. The NORLEI did not forecast accurately in terms of average RMSE for all horizons. Furthermore, the NORLEI did not outperform the benchmark AR model. This implies that our NORLEI was not able to forecast Norwegian GDP growth accurately.

To conclude, we were able to outperform the AR benchmark model by forecasting using Principal Component Analysis in the period 2014q2 to 2018q1. The Production category outperformed the benchmarks, and the other categories. Thus, this category is able to accurately forecast Norwegian GDP growth. Moreover, the All Variables category performed the second most accurate forecasts, for all horizons. Our NORLEI did not perform accurate as a forecast model for Norwegian GDP growth.

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Appendix

Appendix 1: List of variables

The table below shows the variables sorted by category and how they are transformed in terms of frequency and to obtain stationarity. The data is collected from Macrobond. The sources in the table is where Macrobond have collected their data.

For the transformation column, we have the following codes for stationarity transformation:

1 = No differencing
2 = First difference in logarithms
3 = First difference
4 = Double difference in logarithms

To obtain quarterly frequency of the data, the following changes has been made:

EOP = Quarterly end of period
AVG = Quarterly average
SUM = Quarterly sum
N/A = Published quarterly, no changes made

Source	Variables	Transformation	Frequency
	Consumption*		
Statistics Norway	Households Consumption of Goods, Index	2	EOP
Statistics Norway	Households Consumption of Goods, Purchases of Vehicles & Petrol, Index	2	EOP
Statistics Norway	Households Consumption of Goods, Other Goods, Index	2	EOP
Statistics Norway	Households Consumption of Goods, Food, Beverages & Tobacco, Index	2	EOP
Statistics Norway	Households Consumption of Goods, Electricity & Heating Fuels, Index	2	EOP
	* The category consumption is not used as a separate forecast category, but is included in the All Variables category.		
	Employment		
Statistics Norway	Unemployment, Registered	3	N/A
Statistics Norway	Unemployment, Rate, Males & Females	3	EOP
Statistics Norway	Costs & Hours Worked, Hours Worked, Employees	2	N/A
Statistics Norway	Costs & Hours Worked, Hours Worked, Employed & Self Employed	2	N/A
Statistics Norway	Population, Males & Females, Total 15-74 Years	2	N/A
Statistics Norway	Non-Labor Force, Males & Females, Total 15-74 Years	2	N/A
Statistics Norway	Labor Force Rate, Males & Females, Total 15-74 Years	3	N/A
Statistics Norway	Labor Force, Males & Females, Total 15-74 Years	2	N/A
Statistics Norway	Inactivity Rate, Males & Females, Total 15-74 Years	3	N/A
Statistics Norway	Employment, Rate, Males & Females, Total 15-74 Years	3	N/A
Statistics Norway	Employed & Self Employed, Males & Females, Total	2	N/A
	Export/Import		
Statistics Norway	Import, Total, Constant Prices	2	N/A
Statistics Norway	Export, Total, Constant Prices	2	N/A
Statistics Norway	Export, Services, Financial & Business Services, Constant Prices	2	N/A
Statistics Norway	Export, Services, Gross Receipts, Shipping, Constant Prices	2	N/A
Statistics Norway	Export, Services, Other Services, Constant Prices	2	N/A
Statistics Norway	Export, Goods, Agriculture, Forestry & Fishing, Constant Prices	2	N/A
Statistics Norway	Export, Goods, Crude Oil & Natural Gas, Constant Prices	2	N/A
Statistics Norway	Export, Goods, Food Products, Beverages & Tobacco, Constant Prices	2	N/A
Statistics Norway	Export, Goods, Manufacturing Products, Constant Prices	2	N/A

Statistics Norway	Export, Goods, Other Goods excl. Refined Petroleum Products, Constant Prices	2	N/A
Statistics Norway	Import, Services, Financial & Business Services, Constant Prices	2	N/A
Statistics Norway	Import, Services, Gross Receipts, Shipping, Constant Prices	2	N/A
Statistics Norway	Import, Services, Other Services, Constant Prices	2	N/A
Statistics Norway	Import, Services, Petroleum Activities, Various Services, Constant Prices	2	N/A
Statistics Norway	Import, Goods, Food Products, Beverages & Tobacco, Constant Prices	2	N/A
Statistics Norway	Import, Services, Travel, Constant Prices	2	N/A
Statistics Norway	Import, Goods, Manufacturing Products, Constant Prices	2	N/A
Statistics Norway	Import, Goods, Other Goods excl. Refined Petroleum Products, Constant Prices	2	N/A
Statistics Norway	Import, Goods, Textiles, Wearing Apparel, Leather, Constant Prices	2	N/A
Statistics Norway	Export, Services, Petroleum Activities, Various Services, Constant Prices	2	N/A
	Foreign Financials		
Deutsche Boerse	Deutsche Boerse, DAX 30 Index, EUR	2	AVG
Eurostat	Euro Area, GDP, EUR	2	N/A
U.K. ONS	UK, GDP, GBP	2	N/A
U.S. BEA	US, GDP, USD	2	N/A
NASDAQ OMX	Nasdaq, 100 Index, USD	2	AVG
S&P Dow Jones	Dow Jones, Industrial Index, USD	2	AVG
S&P Dow Jones	S&P500 Index, USD	2	AVG
FTSE	FTSE100 Index, GBP	2	AVG
U.S. Department of Treasury	US Bond, 10 Year, Yield	3	AVG
U.S. Department of Treasury	US Bond, 3 Month, Yield	3	AVG
U.S. Department of Treasury	US Spread, 10 Year-3 Month	3	AVG
	Government Statistics		
Statistics Norway	Taxes & Subsidies on Products, Constant Prices	2	N/A
Statistics Norway	Production Approach, Output, Constant Prices	2	N/A
Statistics Norway	Production Approach, Intermediate Consumption, Current Prices	2	N/A
Statistics Norway	Wages & Salaries, Current Prices	2	N/A
Statistics Norway	Compensation of Employees, Current Prices	2	N/A
Statistics Norway	Total Use of Goods & Services, Constant Prices	2	N/A
Statistics Norway	Gross Fixed Capital Formation, Constant Prices	2	N/A
Statistics Norway	Final Domestic Use of Goods & Services, Constant Prices	2	N/A

Statistics Norway	Final Demand from Mainland, Total excl. Changes in Stocks, Constant Prices	2	N/A
Statistics Norway	Final Consumption Expenditure, Constant Prices	2	N/A
Statistics Norway	International Reserves, Official Reserve Assets	2	N/A
Statistics Norway	Central Government Budget, Revenues	2	N/A
Statistics Norway	Central Government Budget, Expenditures	2	N/A
Statistics Norway	Central Government Budget, Net Cash Flow from Petroleum Activities	2	N/A
Statistics Norway	Public Debt, Central Government	2	N/A
	Housing		
Statistics Norway	Dwellings, Total National, Completed	2	SUM
Statistics Norway	Utility Floor Space, Dwellings, Total National, Completed	2	SUM
Statistics Norway	Construction Status, Number, Start, Dwellings	2	SUM
Statistics Norway	Construction Status, Utility Floor Space, Starts, Dwellings	2	SUM
Statistics Norway	Construction Status, Other Buildings, Starts, Dwellings	2	SUM
Statistics Norway	Construction Status, Dwellings, Under Construction	2	SUM
Statistics Norway	Construction Status, Utility Floor Space, Under Construction	2	SUM
Statistics Norway	Real Estate Indicators, Personal Disposable Income	2	AVG
Statistics Norway	Real Estate Prices, Existing Dwellings, Pure Price Index	2	N/A
Statistics Norway	Real Estate Prices, Existing Dwellings, Pure Price Oslo Index	2	N/A
Statistics Norway	Real Estate Prices, Existing Flats, Pure Price Index	2	N/A
Statistics Norway	Real Estate Prices, Existing Single-Family Houses - Detached, Pure Price Index	2	N/A
Statistics Norway	Real Estate Prices, Existing Single-Family Houses - Terraced, Pure Price Index	2	N/A
Statistics Norway	Real Estate Prices, Long-Term, Residential, Price Index	2	N/A
Statistics Norway	Real Estate Prices, Real, Residential, Price Index	2	N/A
Statistics Norway	Real Estate Prices, Detached Houses, New, Change Y/Y, Residential	1	N/A
	Interest Rates & Swaps (Norwegian)		
Norges Bank	Bond, 3 Year	3	AVG
Norges Bank	Bond, 2 Year	3	AVG
Norges Bank	Bill, 3 Month	3	AVG
Norges Bank	Bond, 10 Year	3	AVG
Norges Bank	Bond, 5 Year	3	AVG
Norges Bank	Spread, 10 Year - 3 Month	3	AVG
Norges Bank	Spread, 5 Year - 3 Month	3	AVG
Norges Bank	Spread, 2 Year - 3 Month	3	AVG

Norges Bank	Spread, 3 Year - 3Month	3	AVG
Norges Bank	Overnight Lending Rate	3	AVG
Norges Bank	Central Bank Policy Rate	3	AVG
Oslo Stock Exchange	NIBOR 6 Month	3	AVG
Oslo Stock Exchange	NIBOR 3 Month	3	AVG
Oslo Stock Exchange	Oslo Stock Exchange, Swap Index, 6 Month	4	AVG
Oslo Stock Exchange	Oslo Stock Exchange, Swap Index, 3 Month	4	AVG
Oslo Stock Exchange	Oslo Stock Exchange, Government Bond Index, All Maturities	2	AVG
Oslo Stock Exchange	Oslo Stock Exchange, Government Bill Index, > 180 Day	4	AVG
Oslo Stock Exchange	Oslo Stock Exchange, Government Bill, Index, < 180 Day	4	AVG
	Money & Credit		
Statistics Norway	Interest Rates on Loans	3	N/A
Statistics Norway	Interest Rates on Deposits	3	N/A
Statistics Norway	Interest Margins	3	N/A
Statistics Norway	C1, Domestic Debt	4	EOP
Statistics Norway	C2, Domestic Debt, Non-Financial Corporations	2	EOP
Statistics Norway	C2, Domestic Debt, Municipal Government	2	EOP
Statistics Norway	C2, Domestic Debt, Households	4	EOP
Statistics Norway	C2, Domestic Debt, All Sectors	4	EOP
Statistics Norway	Credit to Non-Financial Sectors, From All Sectors To Households & NPISHs	4	N/A
Statistics Norway	Credit to GDP, From All Sectors To Private Sector	2	N/A
Norges Bank	Central Bank, Liabilities & Equity	2	EOP
Norges Bank	Central Bank, Assets	2	EOP
	Norwegian Financials		
Oslo Stock Exchange	NOK/EUR	2	AVG
Oslo Stock Exchange	NOK/JPY	2	AVG
Oslo Stock Exchange	NOK/SEK	2	AVG
Oslo Stock Exchange	NOK/USD	2	AVG
Norges Bank	NOK, Trade Weighted Exchange Rate	2	AVG
Oslo Stock Exchange	NOK/GBP	2	AVG
Norges Bank	Import-Weighted Krone Index (I-44)	2	AVG
Norges Bank	Nominal Effective Exchange Rate Index, Narrow	2	AVG
Norges Bank	Nominal Effective Exchange Rate Index, Broad	2	AVG
Oslo Stock Exchange	Oslo Stock Exchange, All-Share Index (OSEAX)	2	AVG
Oslo Stock Exchange	Oslo Stock Exchange, Market Cap	2	AVG

Oslo Stock Exchange	Oslo Stock Exchange, Share Trading, Turnover	2	AVG
Oslo Stock Exchange	OSEBX	2	AVG
Intercontinental Exchange	Brent Spot, North Sea	2	AVG
	Other Business Statistics		
Statistics Norway	Bankruptcies, Enterprises, Total	2	SUM
Statistics Norway	Bankruptcies, Personal, Total	2	SUM
Statistics Norway	Bankruptcies, All Industries, Total	2	SUM
Statistics Norway	Wholesale Trade, Total except of Motor Vehicles & Motorcycles	2	N/A
Statistics Norway	Wholesale & Retail Trade & Repair of Motor Vehicles & Motorcycles	2	N/A
Statistics Norway	Vehicle Sales & Registrations, New Registrations, Vehicles	2	SUM
Statistics Norway	Vehicle Sales & Registrations, New Registrations, Private Cars	2	SUM
Statistics Norway	Vehicle Registrations (ACEA), New Passenger Cars	2	SUM
Kantar TNS	Consumer Surveys, Finance Norway, Expectations Barometer	1	AVG
Statistics Norway	Business Surveys, Number of Working Months Covered by Stock of Orders	1	AVG
Statistics Norway	Business Surveys, Indicator on Resource Shortage	1	AVG
Statistics Norway	Business Surveys, Confidence Indicator	1	AVG
Statistics Norway	Business Surveys, Capacity Utilisation	1	AVG
	Production		
Energy Information Administration	Norway, Oil & Gas, Total Oil Supply	2	SUM
Statistics Norway	Mining & Quarrying, Index	2	EOP
Statistics Norway	Metal Production, Crude Steel	2	SUM
Statistics Norway	Manufacturing, Index	2	EOP
Statistics Norway	Industrial Production, Index	2	EOP
Statistics Norway	Capacity Utilization, Manufacturing, Mining & Quarrying	2	N/A
Statistics Norway	Capacity Utilization, Manufacturing	2	N/A
Statistics Norway	Capacity Utilization, Intermediate Goods	2	N/A
Statistics Norway	Capacity Utilization, Consumer Goods	2	N/A
Statistics Norway	Import Prices, Index	2	EOP
	NORLEI		
Statistics Norway	Hours Worked, Employees **	2	N/A
Statistics Norway	Industrial Production, Index **	2	EOP
Norges Bank	Spread, Swap Rate 2 Years - Government Bond 2 Year	1	AVG
Oslo Stock Exchange	Spread, NIBOR 3 Month - Government Bill 3 Month	3	AVG

Norges Bank	Spread, 10 Year - 3 Month **	3	AVG
Oslo Stock Exchange	OSEBX **	2	AVG
Statistics Norway	New Orders	1	N/A
Statistics Norway	Business Tendency Survey, Manufacturing and Mining and Quarrying	1	AVG
Statistics Norway	Construction Status, Number, Start, Dwellings **	2	SUM
Kantar TNS	Consumer Surveys, Finance Norway, Expectations Barometer **	1	AVG

** Variables also included in other categories

Statistics Norway	***Gross Domestic Product, Mainland Norway, Market Values, Constant Prices***	2	N/A

Appendix 2: Full overview of RMSE values

Table: All RMSE values for 4-quarter forecast horizon

4-Quarter Horizon	Forecast Starting Point (t)													Descriptive Statistics			
Categories	2014q1	2014q2	2014q3	2014q4	2015q1	2015q2	2015q3	2015q4	2016q1	2016q2	2016q3	2016q4	2017q1	Average	Minimum	Maximum	Median
AR Benchmark	0.010	0.013	0.013	0.018	0.015	0.025	0.029	0.031	0.021	0.021	0.022	0.018	0.013	0.019	0.010	0.031	0.018
Random Walk	0.012	0.017	0.013	0.015	0.017	0.030	0.028	0.033	0.037	0.057	0.037	0.022	0.036	0.027	0.012	0.057	0.028
All Variables	0.013	0.015	0.008	0.011	0.010	0.020	0.019	0.020	0.016	0.011	0.012	0.012	0.008	0.013	0.008	0.020	0.012
Employment	0.012	0.013	0.010	0.015	0.012	0.021	0.025	0.026	0.017	0.015	0.015	0.014	0.009	0.016	0.010	0.026	0.015
Export/Import	0.010	0.011	0.010	0.017	0.022	0.030	0.034	0.038	0.021	0.023	0.024	0.018	0.009	0.021	0.010	0.038	0.021
Foreign Financials	0.011	0.011	0.010	0.013	0.014	0.031	0.037	0.038	0.028	0.024	0.025	0.020	0.013	0.021	0.010	0.038	0.020
Government Statistics	0.008	0.018	0.018	0.020	0.009	0.023	0.033	0.035	0.036	0.041	0.041	0.038	0.019	0.026	0.008	0.041	0.023
Housing	0.012	0.018	0.015	0.019	0.015	0.025	0.030	0.034	0.018	0.020	0.022	0.015	0.015	0.020	0.012	0.034	0.018
Interest Rates & Swaps	0.010	0.013	0.013	0.017	0.015	0.026	0.031	0.033	0.020	0.019	0.020	0.015	0.012	0.019	0.010	0.033	0.017
Money & Credit	0.010	0.010	0.008	0.015	0.014	0.023	0.026	0.027	0.022	0.026	0.026	0.021	0.013	0.019	0.008	0.027	0.021
NORLEI	0.009	0.013	0.013	0.016	0.011	0.032	0.033	0.034	0.028	0.021	0.021	0.020	0.009	0.020	0.009	0.034	0.020
Norwegian Financials	0.011	0.013	0.013	0.020	0.015	0.031	0.033	0.035	0.021	0.018	0.018	0.014	0.012	0.020	0.011	0.035	0.018
Other Business Statistics	0.007	0.009	0.008	0.010	0.011	0.025	0.028	0.029	0.024	0.024	0.026	0.025	0.014	0.018	0.007	0.029	0.024
Production	0.007	0.009	0.011	0.010	0.008	0.008	0.017	0.018	0.017	0.020	0.017	0.016	0.013	0.013	0.007	0.020	0.013

Table: All RMSE values for 8-quarter forecast horizon

8-Quarter horizon	Forecast Starting Point (t)									Descriptive Statistics			
Categories	2014q1	2014q2	2014q3	2014q4	2015q1	2015q2	2015q3	2015q4	2016q1	Average	Minimum	Maximum	Median
AR Benchmark	0.013	0.018	0.021	0.021	0.021	0.024	0.024	0.025	0.019	0.021	0.013	0.025	0.021
Random Walk	0.013	0.021	0.021	0.021	0.025	0.031	0.023	0.029	0.027	0.024	0.013	0.031	0.023
All Variables	0.011	0.016	0.014	0.015	0.015	0.018	0.017	0.018	0.014	0.015	0.011	0.018	0.015
Employment	0.012	0.016	0.018	0.018	0.017	0.020	0.020	0.020	0.014	0.017	0.012	0.020	0.018
Export/Import	0.014	0.021	0.025	0.025	0.028	0.029	0.029	0.031	0.020	0.025	0.014	0.031	0.025
Foreign Financials	0.012	0.021	0.025	0.025	0.026	0.030	0.030	0.031	0.024	0.025	0.012	0.031	0.025
Government Statistics	0.013	0.018	0.023	0.023	0.027	0.041	0.041	0.044	0.043	0.030	0.013	0.044	0.027
Housing	0.014	0.019	0.021	0.022	0.021	0.024	0.024	0.027	0.017	0.021	0.014	0.027	0.021
Interest Rates & Swaps	0.013	0.018	0.021	0.022	0.021	0.024	0.024	0.026	0.017	0.021	0.013	0.026	0.021
Money & Credit	0.012	0.016	0.018	0.019	0.021	0.025	0.024	0.025	0.020	0.020	0.012	0.025	0.020
NORLEI	0.011	0.020	0.023	0.023	0.025	0.031	0.029	0.030	0.024	0.024	0.011	0.031	0.024
Norwegian Financials	0.013	0.021	0.024	0.025	0.024	0.027	0.026	0.027	0.019	0.023	0.013	0.027	0.024
Other Business Statistics	0.009	0.017	0.018	0.018	0.022	0.028	0.027	0.028	0.023	0.021	0.009	0.028	0.022
Production	0.007	0.008	0.013	0.013	0.013	0.015	0.015	0.016	0.015	0.013	0.007	0.016	0.013

Table: All RMSE values for 12-quarter forecast horizon

12-Quarter Horizon	**Forecast Starting Point (t)**					**Descriptive Statistics**			
Categories	2014q1	2014q2	2014q3	2014q4	2015q1	Average	Minimum	Maximum	Median
AR Benchmark	0.018	0.020	0.020	0.021	0.019	0.020	0.018	0.021	0.020
Random Walk	0.019	0.024	0.021	0.021	0.023	0.021	0.019	0.024	0.021
All Variables	0.015	0.017	0.016	0.016	0.014	0.015	0.014	0.017	0.016
Employment	0.016	0.017	0.017	0.017	0.016	0.017	0.016	0.017	0.017
Export/Import	0.022	0.025	0.025	0.025	0.026	0.024	0.022	0.026	0.025
Foreign Financials	0.018	0.024	0.024	0.025	0.024	0.023	0.018	0.025	0.024
Government Statistics	0.023	0.032	0.033	0.035	0.035	0.031	0.023	0.035	0.033
Housing	0.018	0.021	0.021	0.021	0.020	0.020	0.018	0.021	0.021
Interest Rates & Swaps	0.018	0.020	0.020	0.020	0.019	0.020	0.018	0.020	0.020
Money & Credit	0.017	0.020	0.020	0.020	0.020	0.020	0.017	0.020	0.020
NORLEI	0.020	0.024	0.024	0.024	0.024	0.023	0.020	0.024	0.024
Norwegian Financials	0.020	0.022	0.022	0.023	0.022	0.022	0.020	0.023	0.022
Other Business Statistics	0.017	0.022	0.023	0.023	0.023	0.022	0.017	0.023	0.023
Production	0.011	0.013	0.014	0.013	0.013	0.013	0.011	0.014	0.013

Appendix 3: Seasonal adjustment, Pindyck & Rubinfeld (1998)

The Pindyck Rubinfeld method assumes that any given variable can be separated into four components as shown in the following formula:

$$y_t = L\ x\ S\ x\ C\ x\ I$$

Where:

y_t = Variable at time t
L = Value of the long-term secular trend in series
S = Value of seasonal component
C = (long-term) cyclical component
I = irregular component

Next, a moving average is calculated as a proxy for the combined long-term trend and cyclical component. A moving average of 4 quarters is presumably free of the irregular and seasonal component.

$$\hat{y}_t = \frac{1}{4}(y_{t+2} + y_{t+1} + y_t + y_{t-1})$$

As we assume y_t = L x C, this part of the original equation can be removed.

$$\frac{L\ x\ S\ x\ C\ x\ I}{L\ x\ C} = S\ x\ I = \frac{y_t}{\hat{y}_t} = z_t$$

The Irregular component is eliminated next by averaging the values for the same quarter for all periods and all 4 quarters. This is to smooth out the irregular component over the time-period.

$$\hat{z}_1 = \frac{1}{4}(z_1 + z_5 + z_9 + z_{13} + \cdots + z_T)$$

$$\hat{z}_2 = \frac{1}{4}(z_2 + z_6 + z_{10} + z_{13} + \cdots + z_T)$$

$$\hat{z}_3 = \frac{1}{4}(z_3 + z_7 + z_{11} + z_{14} + \cdots + z_T)$$

$$\hat{z}_4 = \frac{1}{4}(z_4 + z_8 + z_{11} + z_{15} + \cdots + z_T)$$

The $\hat{z}_t$ corresponds to the seasonal component, which is removed by dividing the observed value of the variable by the corresponding seasonal component.

$$\frac{y_1}{\hat{z}_1}, \frac{y_2}{\hat{z}_2}, \frac{y_3}{\hat{z}_3}, \frac{y_4}{\hat{z}_4}, \frac{y_5}{\hat{z}_1}, \frac{y_6}{\hat{z}_2} \cdots$$

This result in a series where the seasonal component is removed.

Appendix 4: Procedure for calculating the LEI

The index is created using the following six-step procedure (The Conference Board, 2019):

The first step is to calculate the month to month changes for each variable. Depending on which form the variables values are given, different methods has been used. A simple arithmetic difference $(x_t=X_t-X_{t-1})$ can be used, if the variable is given in percentage form. If the variable is not in percentage form a symmetric percentage formula is used; $x_t=200*(X_t-X_{t-1})/(X_t+X_{t-1})$. The difference between this series and the standard percentage change formula is that positive and negative changes are threated symmetrically. When a variable is given as a diffusion index or interest rate spread the monthly level can be used. $(x_t=X_t)$.

The second step is to find the monthly contributions adjusted to equalize the volatility for each variable. This is done by calculating a standardization factor, which is the inverted volatility weighted so that the sum of all variables' standardization factors equals one. First, we invert the volatility ($w_x=1/v_x$) for each variable. Then the sum of the inverted volatility ($k=\Sigma\ w_x$) is calculated. Next, all the variables standardization factors are adjusted to sum to one ($r_x=(1/k)*w_x$). Now the adjusted monthly contribution can be found by multiplying the standardization factor with the value of the variables ($m_t=r_x*x_t$).

The third step is to find the index's value by adding the monthly contributions of the variables found in the second step ($i_t=\Sigma\ m_{x,t}$). This sum gives the monthly growth rate of the index.

The fourth step is adding the growth rates adjusted for the trend of a coincident index to the index's value $(i_t'=i_t+a)$. For the leading index the adjustment factor is found by taking the average growth rate of the coincident index for the whole period, subtracted from the average growth rate from the entire period for the leading index.

The fifth step is to use a symmetric percentage formula to find the level of the index and start with an initial value of 100 $(I_1=100)$ for the value of the sample set. $I_n=I_{n-1}*(200+i_n)/(200-i_n)$

The sixth step is to get the index to rebase to average 100 in the base year, by dividing each year by the average of the base year and multiplying by a hundred.