

# Forecasting Swedish GDP Growth

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# Summary

**Title:** Forecasting Swedish GDP Growth

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**Keywords:** Forecasting, GDP, surveys, leading indicators

**Purpose:** The purpose of this thesis is to determine the best linear time series model for forecasting Swedish real GDP growth. The study evaluates the performance of random walk, pure autoregressive and vector autoregressive models that use forward looking surveys as explanatory variables.

**Methodology:** The forecast comparison uses quarterly data for Swedish real GDP from 1993:1 to 2006:4. The forecasts from the different models are generated using an expanding information window approach and the different models are evaluated using standard forecast evaluation criteria.

**Conclusion:** The empirical analysis leads to the conclusion that the vector autoregressive model with 1 lag and confidence in the manufacturing industry as explanatory variable performs best for forecast horizon  $t+1$ , that the vector autoregressive model with 2 lags and consumer confidence as explanatory variable performs best for forecast horizon  $t+4$ , and that the vector autoregressive model with 3 lags and consumer confidence as explanatory variable performs best for forecast horizons  $t+8$  and  $t+12$ . Nonetheless, the performance differences are small and the best models are not statistically significantly better than the second best models for any forecast horizon.

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# 1 Introduction

Forecasts of macroeconomic variables are crucial to many agents in the economy, including economic policymakers. The most important macroeconomic variables to forecast include the Gross National Product (GDP), inflation, and unemployment. As an aggregate measure of total economic production for a country, GDP is one of the primary indicators used to gauge the country's economy, and because of what the measure represents it has a large impact on nearly everyone within that country's economy. Because important economic and political decisions are based on forecasts of these macroeconomic variables, it is imperative that they are as reliable and accurate as possible. Inaccurate forecasts may result in destabilizing policies and a more volatile business cycle.

Due to the important nature of the subject, extensive research has been done and studies have examined many aspects related to macroeconomic forecasting. The research includes studies on the use of direct and iterated forecasting methods (Marcellino et al. 2006), linear and nonlinear models (Binner et al. 2005), and whether explanatory variables improve forecast accuracy (Ang et al. 2007). Most of the research available focuses on forecasting US macroeconomic variables and particularly US inflation.

There are several comprehensive studies comparing methods of forecasting. Marcellino et al. (2006) compares the direct and iterated forecasting methods from linear univariate models based on US macroeconomic time series such as unemployment, interest rate and wages. Their results indicate that the indirect forecasting method generally does better. Banerjee et al. (2003) compares the forecasting accuracy of models using leading indicators and simple autoregressive models for forecasting US inflation and GDP growth. Their results indicate that pure autoregressive models perform best. Ang et al. (2007) examines whether macroeconomic variables, asset markets, or surveys best forecasts out-of-sample U.S. inflation. Their results indicate that surveys best forecasts out-of-sample U.S. inflation. As for research on Swedish macroeconomic variables, Grahn (2006) examines whether the GDP-gap forecasts Swedish inflation better than the unemployment gap. His results indicate that the GDP-gap better forecasts Swedish inflation. Hansson et al. (2003) use a Dynamic Factor Model (DFM) to examine whether data from business tendency surveys are useful for

forecasting Swedish macroeconomic variables and primarily real GDP growth. Their findings show that in most cases the DFM with business tendency surveys outperforms the competing alternatives for forecasting real GDP growth.

The bulk of Swedish GDP forecasts (as well as forecasts of inflation and unemployment) are made by Konjunkturinstitutet and the Riksbank. The models employed by Konjunkturinstitutet and the Riksbank are extremely complex, and are neither available nor practically feasible to researchers carrying out applied work. However, forecasts made from simple models are often only marginally less accurate than forecasts made from more complex alternatives, and Granger and Newbold (1986) argue that only when the benefits of the complex techniques outweigh the additional costs of using them should they be the preferred choice.

This thesis examines whether vector autoregressive models that use forward looking surveys as explanatory variables perform better than random walk and pure autoregressive models for forecasting Swedish real GDP growth. The motive for using forward looking survey data in the vector autoregressive models is that surveys tend to yield improved forecasts for macroeconomic variables (Ang et al. 2007). The forward looking properties of the surveys should sensibly qualify the explanatory variables as being leading indicators of total economic production as measured by GDP.

The forecast comparison is conducted using quarterly Swedish real GDP data from 1993:1 to 2006:4. The iterated multi-period-ahead time series forecast performance of random walk (RW), autoregressive (AR), and vector autoregressive (VAR) models is evaluated. The in-sample data used for initial parameter estimation ranges from 1993:1 to 1999:4, leaving 28 observations for forecast evaluation. The models are used to make out-of-sample forecasts for forecast horizons  $t+1$ ,  $t+4$ ,  $t+8$  and  $t+12$ . The forecasts are evaluated using standard forecast evaluation criteria: Mean Errors (ME), Mean Absolute Errors (MAE) and Root Mean Square Errors (RMSE). The difference in forecast performance is tested for significance using an  $F$ -test.

The empirical analysis finds that the vector autoregressive model with 1 lag and confidence in the manufacturing industry as explanatory variable performs best for forecast horizon  $t+1$ , that the vector autoregressive model with 2 lags and consumer confidence as explanatory variable performs best for forecast horizon  $t+4$ , and that the vector autoregressive model with 3 lags and consumer confidence as explanatory variable performs best for forecast horizons  $t+8$  and  $t+12$ . Nonetheless, the performance differences are small and the best models are not significantly better than the second best models for any forecast horizon.

The structure of the thesis is as follows: Section 2 describes the theoretical aspects, Section 3 describes the data, Section 4 deals with the methodology, Section 5 presents the results and comparisons, and the conclusions drawn are summarized in Section 6.

## 2 Theory

### 2.1 Time series modelling

There is limited knowledge about the economic processes that generate observed data and models have been developed to try and explain these processes. There are two different approaches; models formulated by economic theory and tested using econometric techniques, and models based on statistical theory that try to characterize the statistical process whereby the data were generated (Verbeek, 2004).

The main reason for estimating econometric models is often so that the estimated model can be used to make forecasts of the modeled data. Because forecasts made from simple linear univariate models often are more accurate or only marginally less accurate than forecasts from more complex alternatives, univariate time series models such as pure AR models have proved to be the most popular (Harris & Sollis, 2005).

AR models belong to the statistical model type. The model states that a variable  $y_t$  is generated by its own past together with a residual term  $e_t$ . The residual term represents the influence of all exogenous variables and is assumed to be random such that  $e_t$  has zero mean  $[E(e_t) = 0]$ , constant variance  $[E(e_t^2) = \sigma^2]$ , and no autocorrelation  $[E(e_t e_{t-i}) = 0]$

(Harris & Sollis, 2005). The statistical properties of  $e_t$  imply that  $y_t$  can be treated as a stochastic variable.

A stationary univariate  $p$ -th order (where  $y_t$  depends on past values of  $y$  up to a lag length of  $p$ ) AR model is formulated:

$$y_t = a + b_1 y_{t-1} + b_2 y_{t-2} + \dots + b_p y_{t-p} + e_t \quad (2.1)$$

where  $y_t, y_{t-1}, y_{t-2}$  and  $y_{t-p}$  are lagged values of the dependant variable  $y$  and  $a$  is a constant.

AR models require stationary time series and the Dickey-Fuller (DF) test (Dickey & Fuller, 1979) and Augmented Dickey-Fuller (ADF) test can be used to test for the presence of unit roots, where the presence of a unit root implies a non-stationary time series. Although unit roots are not tested for, forecasting Swedish real GDP growth implies that the time series containing real GDP is differenced once, resulting in a stationary series provided an order of integration equal to at most one.

## 2.2 Forecasting with time series models

Two types of forecast methods exist; the direct and iterated forecast methods (Enders, 2004). The most commonly used type is the iterated multi-period-ahead forecast method where forecasts are made using the one-period-ahead model which is iterated forward the desired number of periods. The direct forecast method uses a horizon-specific estimated model to make multi-period-ahead forecasts. In this thesis the iterated multi-period-ahead forecast method is used together with AR and VAR models.

The iterated multi-period-ahead forecast method with time series models is illustrated using the AR(1) (2.2) and VAR(1) (2.3) model.

$$y_t = \hat{a} + \hat{b}y_{t-1} + \hat{e}_t \quad (2.2)$$

$$y_t = \hat{a} + \hat{b}y_{t-1} + \hat{c}x_{t-1} + \hat{e}_t \quad (2.3)$$

The parameters of (2.2) and (2.3) are estimated using Ordinary Least Squares (OLS), yielding the univariate and multivariate one-step-ahead forecast equations (2.4) and (2.5).

$$E_t(y_{t+1}) = \hat{a} + \hat{b}y_t \quad (2.4)$$

$$E_t(y_{t+1}) = \hat{a} + \hat{b}y_t + \hat{c}x_t \quad (2.5)$$

For forecast horizons greater than one, (2.4) and (2.5) are iterated forward the desired number of periods. The iterated forecast method implies that forecasts of horizons greater than one can be based on both actual and forecasted values of the dependant and explanatory variables.

### **2.3 Leading indicators**

Leading indicators are variables containing information about how other variables are likely to change in a future time period. The VAR models in this thesis use historical values of forward looking surveys as explanatory variables. The motive for using forward looking survey data in the VAR models is that surveys tend to yield improved forecasts for macroeconomic variables (Ang et al. 2007). The intuition is that forward looking surveys, in this case business and consumer confidence surveys, are leading indicators of GDP.

There are many surveys available on the optimism of businesses and consumers on current conditions and future expectations of the economy. The Swedish National Institute of Economic Research publishes a comprehensive monthly report called the Economic Tendency Survey that compiles businesses and consumers view of the economy. The report contains the Economic Tendency Indicator, the Business Tendency Survey and the Consumer Tendency Survey.

The Consumer Tendency Survey is a monthly household survey where 1,500 Swedish households are interviewed. The survey provides a quick qualitative indication of household



plans to purchase durable goods and consumer sentiment on the economic situation in Sweden, personal finances, inflation and saving (Konjunkturinstitutet, 2007). The Business Tendency Survey is a survey conducted in the business sector where 3,000-7,000 firms in the business sector are interviewed on actual outcomes, the current situation and future expectations. It is intended to provide a quick qualitative indication of actual outcomes and expectations regarding central economic variables for which no quantitative data are yet available (Konjunkturinstitutet, 2007). The variables in the survey include new orders, output, and employment. A more extensive quarterly survey is conducted in January, April, July, and October where the difference between the quarterly and the monthly survey is that the quarterly survey covers a larger sample of firms and more questions. The Economic Tendency Indicator is based on the monthly surveys of households and firms and captures the sentiment among these agents in the Swedish economy; the indicator is based on the information contained in the confidence indicators for industry, the service sector, construction, the retail trade and consumers (Konjunkturinstitutet, 2007). The Economic Tendency Indicator can be compared most closely with the EU Commission's Economic Sentiment Indicator (ESI).

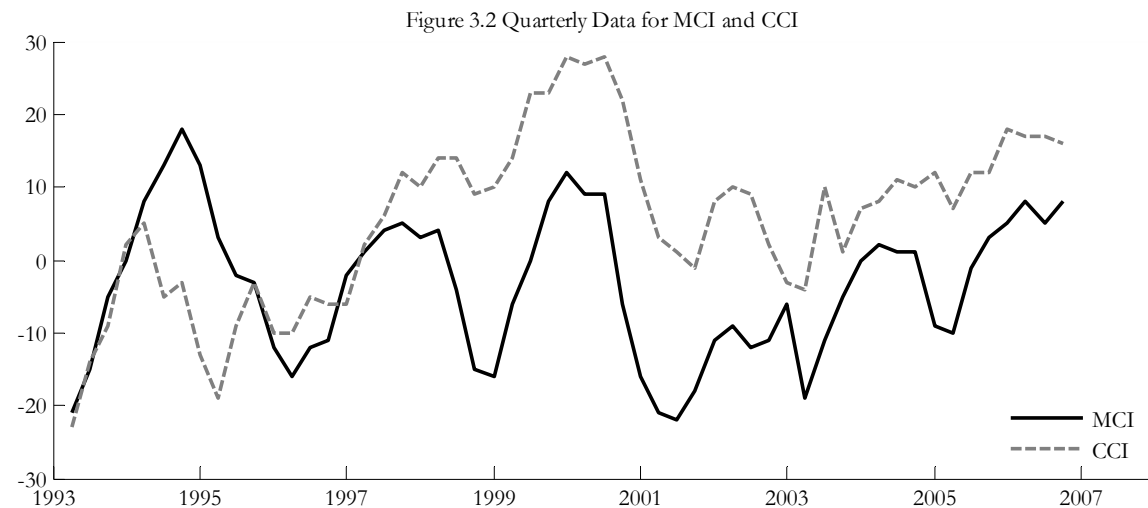
The explanatory variables used in the VAR models are the Consumer Confidence Index (CCI) and the Manufacturing Industry Confidence Index (MCI). Both measures are so-called net percentages, which show the proportion of consumers and firms indicating a positive change in a particular variable, less the proportion indicating a negative change (Konjunkturinstitutet, 2007). The CCI is found in the Consumer Tendency Survey and is defined as the consumers' degree of optimism on current conditions and future (the next 12 months) expectations of the economy. The MCI is found in the Business Tendency Survey and is defined as the degree of optimism on current conditions and future expectations in the manufacturing industry.

### **3 Data**

Seasonally adjusted quarterly data (1993:1-2006:4) for Swedish real GDP is taken from Statistics Sweden (SCB). To obtain the data for the dependant variable, Swedish real GDP growth, the seasonally adjusted quarterly data for real GDP is log differenced.

$$\Delta y_t = \ln(Y_t) - \ln(Y_{t-1}) \quad (3.1)$$

For the explanatory variables, the forward looking surveys, seasonally adjusted data of quarterly frequency (1993:1-2006:4) for MCI and of monthly frequency (1993:1-2006:12) for CCI is taken from Konjunkturinstitutet (KI). The monthly data for CCI is converted into quarterly data through averaging.



From Figures 3.1 and 3.2, it appears that real GDP growth and MCI are coincident; the variables appear synchronized and the peaks and troughs in line with one another. The only evident exceptions occur in 1999 and 2006, where the troughs in MCI do not reflect similar troughs in real GDP growth. Real GDP growth and CCI do not appear to exhibit the same

degree of synchronization and regular co-movement as do real GDP growth and MCI. The co-movement appears to be irregular and CCI seems to at different times be leading, coinciding and lagging real GDP growth.

## 4 Methodology

### 4.1 Forecasting

The time series containing  $\Delta y$  is divided into in-sample (1993:1 to 1999:4) and out-of-sample (2000:1 to 2006:4) data. The in-sample data is used for initial parameter estimation and the out-of-sample data is used for forecast evaluation. The AR and VAR models with 1-4 lags are used to forecast out-of-sample  $\Delta y$  for forecast horizons  $t+1$ ,  $t+4$ ,  $t+8$  and  $t+12$ . Also, RW models are used as benchmarks to forecast out-of-sample  $\Delta y$  for forecast horizons  $t+1$ ,  $t+4$ ,  $t+8$  and  $t+12$ .

The RW model forecasts are given by:

$$E_t(\Delta y_{t+h+1}) = \Delta y_{t+h} \quad (4.1)$$

The AR(1) model forecasts are given by:

$$E_t(\Delta y_{t+h+1}) = \hat{a} + \hat{b}\Delta y_{t+h} \quad (4.2)$$

The VAR(1) model forecasts are given by:

$$E_t(\Delta y_{t+h+1}) = \hat{a} + \hat{b}\Delta y_{t+h} + \hat{c}x_{t+h} \quad (4.3)$$

where  $b$  is the forecast horizon and  $x$  either MCI or CCI. For lag lengths greater than 1, lagged values of the dependant variable  $\Delta y$  are added to the AR and VAR models as shown in (2.1).

The one-step-ahead (horizon  $t+1$ ) forecast  $E_t(\Delta y_{t+1})$  is made using the initially estimated model parameters and information available at period  $t$ . Then, for the entire out-of-sample period, the estimated model parameters are updated and all available information used to make one-step-ahead forecasts one period after another.

The  $b$ -step-ahead (horizon  $t+b$ ) forecast  $E_t(\Delta y_{t+h+1})$  uses both actual and forecasted values of  $\Delta y$ . First, the one-step-ahead forecast  $E_t(\Delta y_{t+1})$  is made using the initially estimated model parameters and the information available at period  $t$ . Then, the one-step-ahead forecasting model is iterated forward one period after another until period  $t+b$ . The procedure is repeated for the entire out-of-sample, where the estimated model parameters are updated and all available information at period  $t$  used to make  $b$ -step-ahead forecasts one period after another.

## 4.2 Forecasting accuracy

To determine which model is most accurate the out-of-sample forecast errors are evaluated using common forecast evaluation criteria; ME, MAE and RMSE (Binner et al., 2005). ME is simply the average of the out-of-sample forecast errors and gives an indication as to whether the forecast is biased. MAE is similar to ME but averages the absolute values of the out-of-sample forecast errors. RMSE is the most frequently used measure and is known to be more sensitive to outliers than MAE.

The forecast error ( $\varepsilon$ ) is given by:

$$\varepsilon_t^f = \Delta y_t^f - \Delta y_t \quad (4.4)$$

where  $\Delta y_t^f$  is forecasted  $\Delta y$  and  $\Delta y_t$  is actual  $\Delta y$  at period  $t$ .

The forecast error evaluation criterions are given by:

$$ME = \frac{1}{K} \sum_{t=2000:1+h-1}^{2006:4} \varepsilon_t^f \quad (4.5)$$

$$MAE = \frac{1}{K} \sum_{2000:1+h-1}^{2006:4} |\varepsilon_t^f| \quad (4.6)$$

$$RMSE = \frac{1}{K} \left[ \sum_{2000:1+h-1}^{2006:4} (\varepsilon_t^f)^2 \right]^{\frac{1}{2}} \quad (4.7)$$

where  $K$  is the total number of out-of-sample forecasts and  $h$  is the forecast horizon.

Although ME, MAE and RMSE are calculated for all models and forecast horizons, only RMSE is used when ranking the performance of the models. An  $F$ -test is used to test whether the differences in forecast RMSE are significant (Enders, 2004). The  $F$ -test assumes that the forecast errors have zero mean and are normally distributed, serially uncorrelated and contemporaneously uncorrelated with each other.

The  $F$ -test is formulated (standard  $F$ -distribution with  $H-H$  degrees of freedom):

$$F = \frac{\sum_{i=1}^H e_{1i}^2}{\sum_{i=2}^H e_{2i}^2} \quad (4.8)$$

where the larger of the forecast RMSE is put in the numerator. The null hypothesis is for equal forecasting performance for the two models being compared. The intuition is that the  $F$ -value will equal unity if the forecast RMSE from the two models are equal, while a very large  $F$ -value implies that the forecast RMSE from the first model is substantially larger than the forecast RMSE from the second model (Enders, 2004).

## 5 Results

A MATLAB code was written to perform the computations required to find the best model to forecast  $\Delta y$ . For each forecast horizon the code estimates the models, uses the estimated

models to forecast the out-of-sample, calculates the out-of-sample ME, MAE and RMSE, and ranks the models by the latter. The results generated by the code are presented in Table 5.1, where the models are ranked from best to worst performing based on forecast RMSE.

Table 5.1

$t+1$		$t+4$		$t+8$		$t+12$	
Model	RMSE	Model	RMSE	Model	RMSE	Model	RMSE
VAR <sub>1</sub> (1)	0,0007216	VAR <sub>2</sub> (2)	0,0008141	VAR <sub>2</sub> (3)	0,0008112	VAR <sub>2</sub> (3)	0,0009591
AR(4)	0,0007475	VAR <sub>2</sub> (3)	0,0008178	VAR <sub>2</sub> (2)	0,0008213	RW	0,0009905
AR(1)	0,0007540	AR(2)	0,0008384	AR(3)	0,0008556	VAR <sub>2</sub> (2)	0,0011000
VAR <sub>1</sub> (2)	0,0007656	AR(3)	0,0008478	RW	0,0008616	AR(3)	0,0011000
AR(2)	0,0007665	RW	0,0008512	AR(2)	0,0008621	AR(2)	0,0011000
VAR <sub>2</sub> (1)	0,0007788	VAR <sub>1</sub> (2)	0,0008649	VAR <sub>1</sub> (4)	0,0008932	VAR <sub>1</sub> (2)	0,0011000
AR(3)	0,0007858	VAR <sub>1</sub> (4)	0,000866	VAR <sub>1</sub> (2)	0,0008986	VAR <sub>1</sub> (3)	0,0012000
RW	0,0007930	AR(4)	0,0009079	VAR <sub>1</sub> (3)	0,0009014	VAR <sub>1</sub> (4)	0,0012000
VAR <sub>1</sub> (4)	0,0007985	VAR <sub>2</sub> (1)	0,0009318	AR(4)	0,0009971	AR(4)	0,0013000
VAR <sub>1</sub> (3)	0,0008298	VAR <sub>1</sub> (1)	0,0009664	VAR <sub>2</sub> (1)	0,0011000	VAR <sub>2</sub> (4)	0,0014000
VAR <sub>2</sub> (2)	0,0008533	VAR <sub>1</sub> (3)	0,000972	VAR <sub>1</sub> (1)	0,0011000	VAR <sub>2</sub> (1)	0,0014000
VAR <sub>2</sub> (4)	0,0008927	AR(1)	0,0009736	VAR <sub>2</sub> (4)	0,0011000	VAR <sub>1</sub> (1)	0,0014000
VAR <sub>2</sub> (3)	0,0008931	VAR <sub>2</sub> (4)	0,0010000	AR(1)	0,0012000	AR(1)	0,0015000

Note: VAR<sub>1</sub> is a bivariate model based on MCI and VAR<sub>2</sub> is a bivariate model based on CCI.

Table 5.1 shows that the VAR(1) model with MCI as explanatory variable performs best for forecast horizon  $t+1$ , that the VAR(2) model with CCI as explanatory variable performs best for forecast horizon  $t+4$ , and that the VAR(3) model with CCI as explanatory variable performs best for forecast horizons  $t+8$  and  $t+12$ . The forecasts are plotted in Figures 5.1-4; the forecasts made by the VAR<sub>1</sub>(1) model for forecast horizon  $t+1$  are plotted in Figure 5.1, the forecasts made by the VAR<sub>2</sub>(2) model for forecast horizons  $t+4$  in Figure 5.2, and the forecasts made by the VAR<sub>2</sub>(3) model for forecast horizons  $t+8$  and  $t+12$  in Figures 5.3-4.

Figure 5.1 Forecast horizon t+1, VAR(1) based on MCI

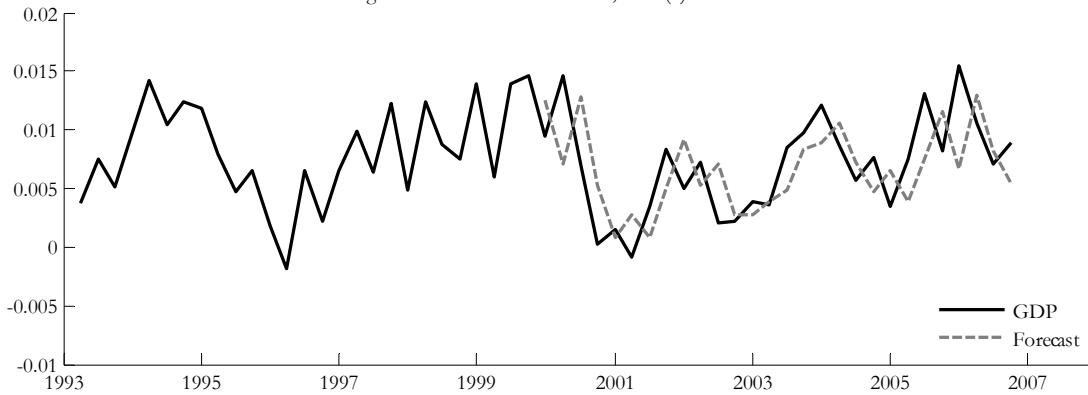


Figure 5.2 Forecast horizon t+4, VAR(2) based on CCI

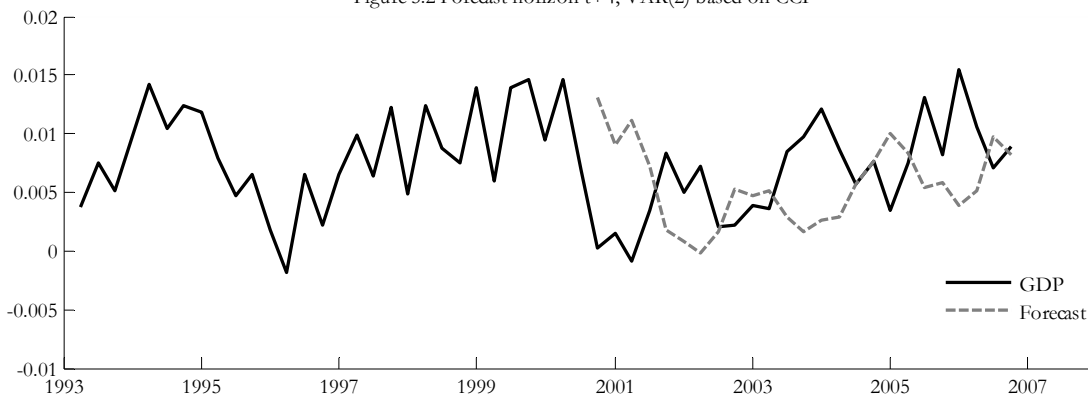


Figure 5.3 Forecast horizon t+8, VAR(3) based on CCI

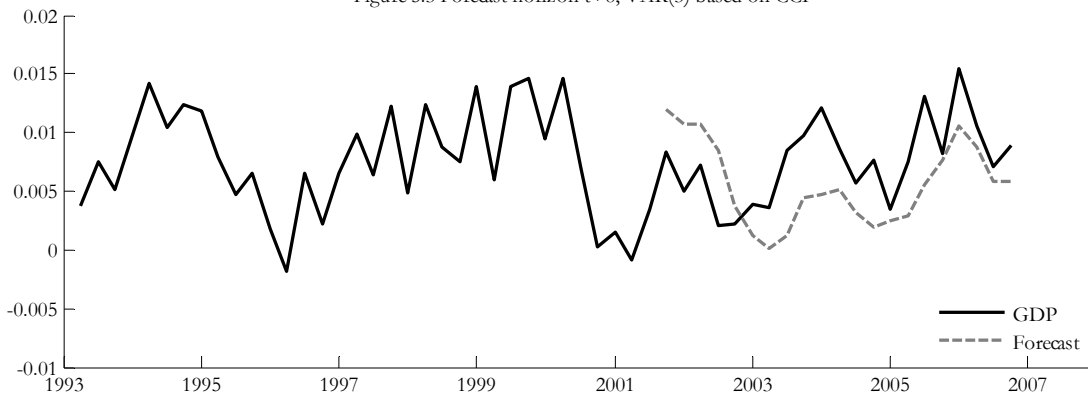
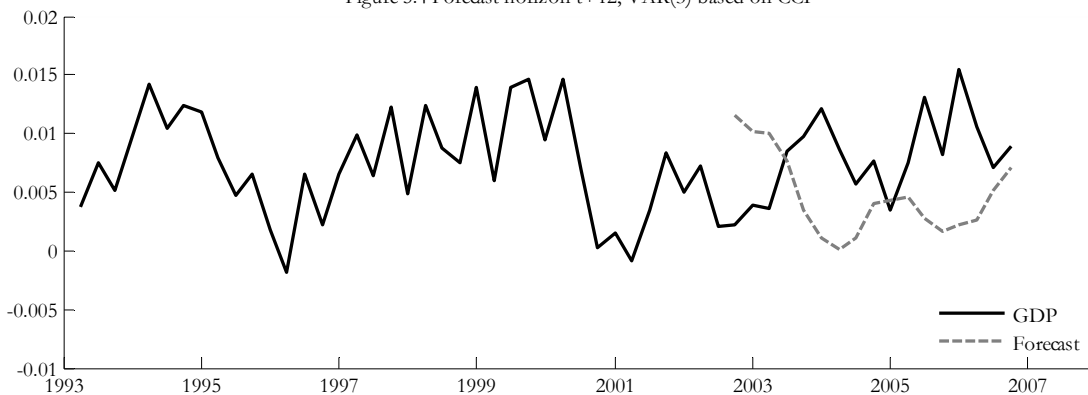


Figure 5.4 Forecast horizon t+12, VAR(3) based on CCI



Using the  $F$ -test described in Section 4.2, the differences in forecast RMSE between the best performing and the second best performing models are tested for significance. The  $F$ -statistics and  $P$ -values of the  $F$ -tests are presented in Table 5.2. Table 5.2 reveals that the best performing models are not significantly better than the second best performing models for any forecast horizon.

Table 5.2

Horizon	Models	F-statistic	P-value
$t+1$	AR(4)/VAR <sub>1</sub> (1)	1,035948	0,463108
$t+4$	VAR <sub>2</sub> (3)/VAR <sub>2</sub> (2)	1,004533	0,495269
$t+8$	VAR <sub>2</sub> (2)/VAR <sub>2</sub> (3)	1,012488	0,487019
$t+12$	RW/VAR <sub>2</sub> (3)	1,032750	0,466329

When comparing the forecast RMSE of the best performing model with the forecast RMSE of the RW benchmark model (the  $F$ -statistics and  $P$ -values of the  $F$ -tests are presented in Table 5.3), the  $F$ -test again shows that it is not significantly lower for any forecast horizon.

Table 5.3

Horizon	Models	F-statistic	P-value
$t+1$	RW/VAR <sub>1</sub> (1)	1,099002	0,40226
$t+4$	RW/VAR <sub>2</sub> (2)	1,045621	0,453439
$t+8$	RW/VAR <sub>2</sub> (3)	1,062169	0,437172
$t+12$	RW/VAR <sub>2</sub> (3)	1,032750	0,466329

Even when comparing the forecast RMSE of the best performing model with the forecast RMSE of the worst performing model (the  $F$ -statistics and  $P$ -values of the  $F$ -tests are presented in Table 5.4), the  $F$ -test shows that it is not significantly lower for any forecast horizon.



Table 5.4

Horizon	Models	$F$ -statistic	$P$ -value
$t+1$	$\text{VAR}_2(3)/\text{VAR}_1(1)$	1,237611	0,288254
$t+4$	$\text{VAR}_2(4)/\text{VAR}_2(2)$	1,228365	0,294984
$t+8$	$\text{AR}(1)/\text{VAR}_2(3)$	1,479326	0,153009
$t+12$	$\text{AR}(1)/\text{VAR}_2(3)$	1,564015	0,121399

Although the differences in forecast RMSE between the models are very small, it may be that the formulated  $F$ -test used is inappropriate, producing incorrect  $F$ -statistics and  $P$ -values. A reason for the inappropriateness of the formulated  $F$ -test could be the non-satisfaction of any one or more of the  $F$ -test assumptions; that the forecast errors have zero mean and are normally distributed, serially uncorrelated, and contemporaneously uncorrelated with each other.

Enders (2004) describes alternative methods for forecast evaluation that relax the mentioned assumptions. The Granger-Newbold test (1976) is an alternative that overcomes the problem of contemporaneously correlated forecast errors, while the Diebold-Mariano (1995) test is an alternative that also overcomes the problem of forecast errors not having a zero mean and normal distribution, and not being serially uncorrelated (Enders, 2004).

The MATLAB code also calculates Akaike's (1974) Information Criterion (AIC) for all models at each period of the out-of-sample and determines the best model at each period based on the value of the information criteria. When using information criteria to find a suitable model, the aim is to minimize the value of the information criteria. For all periods of the out-of-sample the model found most suitable based on the information criteria is the VAR(4) model with MCI as explanatory variable. Clearly, the model suggested based on the information criteria is not coincident with the model suggested based on the out-of-sample forecast RMSE.

## 6 Conclusions

The purpose of this thesis was to determine the best linear time series model to forecast Swedish real GDP growth by comparing the forecast performance of RW, AR and VAR models that use forward looking surveys as explanatory variables. The motive for using forward looking survey data in the VAR models was that surveys tend to yield improved forecasts for macroeconomic variables (Ang et al. 2007). The results show that the VAR(1) model with MCI as explanatory variable performs best for forecast horizon  $t+1$ , that the VAR(2) model with CCI as explanatory variable performs best for forecast horizon  $t+4$ , and that the VAR(3) model with CCI as explanatory variable performs best for forecast horizons  $t+8$  and  $t+12$ .

Although VAR models based on forward looking surveys are found to best forecast Swedish real GDP growth, the differences are small and the best performing models are neither statistically significantly better than the second best performing models, the benchmark models, nor even the worse performing models. As previously mentioned, this may be because the formulated  $F$ -test used is inappropriate, producing incorrect  $F$ -statistics and  $P$ -values. Examining whether the  $F$ , Granger-Newbold, and Diebold-Mariano tests produce different results as regards the forecast evaluation of the models could be of interest.

However, the results could also be due to a bad choice of surveys; the chosen surveys may have weak forward looking properties and not be leading indicators of Swedish real GDP growth. A comparison of a larger number of forward looking surveys and their capacity to forecast Swedish real GDP growth could be relevant. Similarly to Ang et al. (2007), it could also be relevant to examine if surveys are in fact appropriate or if macroeconomic variables better forecasts Swedish real GDP growth. It may be that surveys should not be used.

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## MATLAB code

```

=> function [modelEvaluation modelStructure] =
    linearForecastModelEvaluation(yFbegin,yFend,lags,horizons,data,var1,var2)

    %The function is called to perform the model forecast evaluation on the out-of-
    %sample, specifying where the out-of-sample begins and ends, the lags and horizons
    %to use, and the dependant and explanatory variables.

    [forecastEvaluationAR] =
    univariate_forecastPerformance(data,yFbegin,yFend,lags,horizons);

    [forecastEvaluationVAR1] =
    multivariate_forecastPerformance(var1,yFbegin,yFend,lags,horizons);

    [forecastEvaluationVAR2] =
    multivariate_forecastPerformance(var2,yFbegin,yFend,lags,horizons);

    [forecastEvaluationRW] =
    randomwalk_forecastPerformance(data,yFbegin,yFend,horizons);

    [modelEvaluation] =
    evaluateModels(forecastEvaluationAR,forecastEvaluationVAR1,forecastEvaluationVAR2,
    forecastEvaluationRW,lags,horizons);

    [modelStructure] = lagStructure(data,var1,var2,lags,yFbegin,yFend);

end

=> function [forecastEvaluation] =
    univariate_forecastPerformance(data,yFbegin,yFend,lags,horizons)

    %The function determines out-of-sample forecasts and forecast errors using the pure
    %autoregressive model.

    forecastEvaluation=cell(length(lags),length(horizons));

    for i=1:length(lags)
        for j=1:length(horizons)
            %y yF
            mod]=univariate_forecast(data,yFbegin,yFend,cell2mat(lags(i)),cell2mat(horizons(j))
            );
            [ma mae rmse]=errorCalc(y,yF,yFbegin);
            forecastEvaluation{i,j}.model='AR';
            forecastEvaluation{i,j}.lag=cell2mat(lags(i));
            forecastEvaluation{i,j}.horizon=cell2mat(horizons(j));
            forecastEvaluation{i,j}.ma=ma;
            forecastEvaluation{i,j}.mae=mae;
            forecastEvaluation{i,j}.rmse=rmse;
        end;
    end;

end

=> function [y yF mod] = univariate_forecast(data,yFbegin,yFend,lag,horizon)

    %The function makes out-of-sample forecasts using the pure autoregressive model.

    if (yFbegin<=yFend) && (1<=lag) && (1<=horizon)

        y=timeseries(data,1:length(data),'name','y');
        yF=timeseries('yF');

        for n=yFbegin+horizon-1:yFend
            mod=ar(y.data(1:n-horizon),lag);
            temp=timeseries(data,1:length(data),'name','temp');
            if (horizon>1) && (n-horizon+1<=yFend)
                for l=n-horizon+1:n
                    x=0;
                    for i=1:lag
                        x=x-(mod.parametervector(i)*temp.data(l-i));
                    end;
                    s.data=x;
                    s.time=l;
                    s.overwriteflag=true;
                end;
            end;
        end;
    end;
end

```

```

        temp=addsample(temp,s);
    end;
else
    x=0;
    for i=1:lag
        x=x-(mod.parametervector(i)*y.data(n-i));
    end;
    s.data=x;
end;
s.time=n;
s.overwriteflag=true;
yF=addsample(yF,s);
end;
end;
end

```

```

=> function [forecastEvaluation] =
    multivariate_forecastPerformance(data,yFbegin,yFend,lags,horizons)
    %The function determines out-of-sample forecasts and forecast errors using the
    %vector autoregressive model.

    forecastEvaluation=cell(length(lags),length(horizons));
    for i=1:length(lags)
        for j=1:length(horizons)
            mod]=multivariate_forecast(data,yFbegin,yFend,cell2mat(lags(i)),cell2mat(horizons(j)
            ));
            [ma mae rmse]=errorCalc(y,yF,yFbegin);
            forecastEvaluation{i,j}.lag=cell2mat(lags(i));
            forecastEvaluation{i,j}.horizon=cell2mat(horizons(j));
            forecastEvaluation{i,j}.ma=ma;
            forecastEvaluation{i,j}.mae=mae;
            forecastEvaluation{i,j}.rmse=rmse;
        end;
    end;
end

```

```

=> function [y yF mod] = multivariate_forecast(data,yFbegin,yFend,lag,horizon)
    %The function makes out-of-sample forecasts using the vector autoregressive model.

    if (yFbegin<=yFend) && (1<=lag) && (1<=horizon)
        y=timeseries(data(1:length(data),:),1:length(data),'name','y');
        yF=timeseries('yF');
        delay=1;
        for n=yFbegin+horizon-1:yFend
            mod=arx(y.data(1:n-horizon,:),[lag lag delay]);
temp=timeseries(data(1:length(data),:),1:length(data),'name','temp');
            if (horizon>1) && (n-horizon+1<=yFend)
                for l=n-horizon+1:n
                    x1=0;
                    x2=0;
                    for i=1:lag
                        p=temp.data(l-i,1);
                        x1=x1-(mod.a(i+1)*p);
                        q=temp.data(l-i,2);
                        x2=x2+mod.b(i+delay)*q;
                    end;
                    temp.data(l,1)=x1;
                    temp.data(l,2)=x2;
                    s.data=x1+x2;
                end;
            else
                x1=0;
                x2=0;
                for i=1:lag
                    p=y.data(n-i,1);
                    x1=x1-(mod.a(i+1)*p);
                    q=y.data(n-i,2);
                    x2=x2+mod.b(i+delay)*q;
                end;
            end;
        end;
    end;
end

```

```

        end;
        s.data=x1+x2;
    end;
    s.time=n;
    s.overwriteflag=true;
    yF=addsample(yF,s);
end;
end;

⇒ function [forecastEvaluation] =
randomwalk_forecastPerformance(data,yFbegin,yFend,horizons)

%The function determines out-of-sample forecasts and forecast errors using the
%random walk model.

    forecastEvaluation=cell(1,length(horizons));
    for i=1:length(horizons)
        [y yF]=randomwalk_forecast(data,yFbegin,yFend,cell2mat(horizons(i)));
        [ma mae rmse]=errorCalc(y,yF,yFbegin);
        forecastEvaluation{i}.model='RW';
        forecastEvaluation{i}.horizon=cell2mat(horizons(i));
        forecastEvaluation{i}.ma=ma;
        forecastEvaluation{i}.mae=mae;
        forecastEvaluation{i}.rmse=rmse;
    end;
end;

⇒ function [y yF] = randomwalk_forecast(data,yFbegin,yFend,horizon)

%The function makes out-of-sample forecasts using the random walk model.

    if (yFbegin<=yFend) && (1<=horizon)
        y=timeseries(data,1:length(data),'name','y');
        yF=timeseries('yF');
        for n=yFbegin+horizon-1:yFend
            s.data=y.data(n-horizon);
            s.time=n;
            s.overwriteflag=true;
            yF=addsample(yF,s);
        end;
    end;
end;

⇒ function [y] =
evaluateModels(forecastEvaluationAR,forecastEvaluationVAR1,forecastEvaluationVAR2,f
orecastEvaluationRW,lags,horizons)

%The function evaluates the performance of the models and ranks them according to
%RMSE.

    y=cell(length(horizons),1);
    for k=1:length(horizons)
        x=cell(3*length(lags)+1,1);
        n=0;
        for i=1:length(lags)
            n=n+1;
            x(n)=forecastEvaluationAR(i,k);
            n=n+1;
            x(n)=forecastEvaluationVAR1(i,k);
            x{n}.model='VAR1';
            n=n+1;
            x(n)=forecastEvaluationVAR2(i,k);
            x{n}.model='VAR2';
        end;
        n=n+1;
        x(n)=forecastEvaluationRW(k);
        for i=2:length(x)
            index = cell2mat(x(i));
            j = i;
            while ((j > 1) && (x{j-1}.rmse > index.rmse))
                x(j) = x(j-1);
            end;
        end;
    end;
end;

```

```

        j = j - 1;
    end;
    x(j) = {index};
end;
y(k)={x};
end;
end

```

⇒ function [ma mae rmse] = errorCalc(y,yF,yFbegin)

*%The function calculates the forecast ME, MAE and RMSE.*

```

    sumerrors=0;
    sumerrorsabs=0;
    sumerrorssqrt=0;
    for i=1:length(yF)
        celln=yFbegin+i-1;
        sumerrors=sumerrors+(yF.data(i)-y.data(celln));
        sumerrorsabs=sumerrorsabs+(abs(yF.data(i)-y.data(celln)));
        sumerrorssqrt=sumerrorssqrt+((yF.data(i)-y.data(celln))^2);
    end;
    ma=(1/length(yF))*(sumerrors);
    mae=(1/length(yF))*(sumerrorsabs);
    rmse=(1/length(yF))*((sumerrorssqrt)^(0.5));
end

```

⇒ function [q] = lagStructure(data,var1,var2,lags,yFbegin,yFend)

*%The function determines the best model and lag structure for each period of the %out-of-sample using Aikaike's Information Criterion.*

```

    p=modelAicCalc(data,var1,var2,lags,yFbegin,yFend);
    q=cell(yFbegin-yFend+1,1);
    for j=yFbegin:yFend
        x=p{1};
        for k=1:3*length(lags)
            if p{k}.aic{j}<x.aic{j}
                x=p{k};
            end;
        end;
        s.model=x.model;
        s.lag=x.lag;
        s.aic=x.aic{j};
        q(j) = {s};
    end;
end

```

⇒ function [p] = modelAicCalc(data,var1,var2,lags,yFbegin,yFend)

*%The function determines Aikaike's Information Criterion for all models and periods %of the out-of-sample.*

```

    n=0;
    p=cell(length(lags)*3,1);
    for i=1:length(lags)
        n=n+1;
        p{n}.model = 'AR';
        p{n}.lag = cell2mat(lags(i));
        p{n}.aic = aicCalc(data,yFbegin,yFend,cell2mat(lags(i)),1);
        n=n+1;
        p{n}.model = 'VAR1';
        p{n}.lag = cell2mat(lags(i));
        p{n}.aic = aicCalc(var1,yFbegin,yFend,cell2mat(lags(i)),2);
        n=n+1;
        p{n}.model = 'VAR2';
        p{n}.lag = cell2mat(lags(i));
        p{n}.aic = aicCalc(var2,yFbegin,yFend,cell2mat(lags(i)),2);
    end;
end

```

⇒ function [x] = aicCalc(data,yFbegin,yFend,lag,v)



*%The function calculates Aikaike's Information Criterion for the specified model  
%structure.*

```
delay=1;
x=cell(yFend-yFbegin+1,1);
if v==1
    y=timeseries(data,1:length(data),'name','y');
    for n=yFbegin:yFend
        x{n}=aic(ar(y.data(1:n),lag));
    end;
else
    y=timeseries(data(1:length(data),:),1:length(data),'name','y');
    for n=yFbegin:yFend
        x{n}=aic(arx(y.data(1:n,:),[lag lag delay]));
    end;
end;
end
```



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