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THE YIELD CURVE AS A PREDICTOR OF GDP AND UNEMPLOYMENT: THE CASE OF G7

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ABSTRACT

The yield curve - the difference between the long term bond yield and the short treasury- is one of the most watched financial indicators especially for its forecasting abilities towards the real economy and how it is going to respond. In this paper we re-examine the yield curve and its predicting abilities for GDP and Unemployment rate for the G7 industrial countries. This research contributes taking the most recent years in account for multiple countries. We conclude that for GDP growth the yield curve is still a consistent predictor but it is not the most suitable for the case of Unemployment rate

Key words: Yield curve, spread, GDP growth, Unemployment rate, Forecasting, Out-of-Sample, In-sample, Shocks, Impulse response, economic index

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1. INTRODUCTION

The Yield curve, which plots the Treasury bonds against their own maturity, is one of the closest looked indicator for upcoming economic growth or recession. Many policy makers and investors track carefully the shape of this curve so they can decide their next move or, for policy makers, to take measures for the economy.

The is typically upward sloping and somewhat convex. At times, however, it becomes flat or slopes downward which is usually can be translated as a harbinger of upcoming recession. Because of that the Yield curve has been one staple indicator for forecasting the future economic activity. Financial market participants truly value accurate forecasts, since they can mean the difference between a large profit and a large loss. Financial data are also available more frequently than other statistics.

In this research we examine the ability of the yield curve to predict future economic activity. More specifically if it can predict the GDP movement and that of Unemployment as well as the impact on both of these variables given that they are some of the most important macroeconomic aspects.

There is a wide range of previous research regarding the yield curve. In this work we will focus on the in and out-of-sample forecasting methods of both GDP and Unemployment and then we will explore the impact of shocks between the Yield curve and both GDP and Unemployment. We start with the existing Literature Review, following with the theoretical basis, then the data and finally with the results of our research and conclusive remarks.

2. LITERATURE REVIEW

The yield curve as a means for forecasting economic activity is something that has been occasionally considered before. One of the most crucial factors of the yield curve is the term structure. Estrella, A., & Hardouvelis, G. A. (1991). They presented evidence that the yield curve can predict cumulative changes in real output for 3 years into the future and successive marginal changes in real output changes up to a year and a half into the future. Most of the literature is concentrated in the example of the United States however Bonser-Neal, C., & Morley, T. R. (2002) evaluated the yield spread to measure and forecast the real economic activity using examples of 11 different industrial countries with In sample and Out of sample forecasting methods. Their results indicate the yield spread is a statistically and economically significant predictor of economic activity in several countries besides the United States.

Another attempt by Ang, A., Piazzesi, M., & Wei, M. (2006) presented a model of yields and GDP growth for forecasting GDP. Their approach was motivated from term structure approaches for pricing bonds in a no-arbitrage framework. Following a Vector Autoregressive model found that the factor structure is largely responsible for most of the efficiency gains resulting in better out-of-sample forecasts. In the same sense Smets, F., & Tsatsaronis, K. (1997) investigated the economic determinants of the slope of the yield curve and economic activity in Germany and the United States with the main objective of identifying the sources of the strong leading indicator property of the term spread for future output growth. They found that monetary policy plays a significant role in the relationship between the term structure and output growth. Haubrich, J. G., & Dombrosky, A. M. (1996) confirm with their conclusion that the 10 year, three month spread has substantial predictive results but the relationship between the yield curve and economic activity has worsened. Chinn, M. D., & Kucko, K. J. (2010) find that the predictability of the yield curve has deteriorated over the recent years. In addition they found that the European models perform better for than the non- European ones.

Estrella, A., Rodrigues, A. P., & Schich, S. (2003), examine continuous models, which predict either economic growth or inflation, and binary models, which predict either recessions or inflationary pressure if they are stable with samples of United States and Germany. They summarized that we have to proceed with caution when we choose the model considering stability of the particular model and that it is advisable to test different models as well. Aguiar-Conraria, L., Martins, M. M., & Soares, M. J. (2012) on the other hand find some interesting information using the tools of wavelet analysis presume that there is not consistent role of the yield curve's formation either as leading or coincident indicator for economic activity but it is significant towards the monetary policy. Hu, Z. (1993), one of the few that have evidence for the relationship between the yield curve and the GDP growth for the G7 countries. He applied out-of-sample forecasting method and found that the slope of the yield curve is positively related to the expected growth in real output compared to other predicting variables like stock changes index.

Mehl, A. (2009) in his paper for the yield curve as a predictor for emerging economies, again using in-sample and out-of-sample models and conclude that there is still information on the economic activity from the yield curve, indicating that there are differences in terms o ability of domestic yield curves to predict inflation and growth, an area which has remained under-researched, including for industrial countries. Bauer, M. D., & Mertens, T. M. (2018) in one of the most recent researches for the subject of the yield curve state while the current environment appears unique compared with recent economic history, statistical evidence suggests that the signal in the term spread is not diminished. Estrella and Mishkin (1996) investigating the yield curve as a predictor of recession for the United States suggest that regarding the results they obtained the yield curve spread can have useful role in macroeconomic predictions. Hvozdenská, J. (2017) analyze the dependence between slope of the yield curve and an economic activity of Nordic countries between the years 2000 and 2013. In their research showed that the best predictive lags of spreads are lags of four and five quarters in order to get the best results. Their results confirm that 10-year and 3-month yield spread has a significant predictive power for real GDP growth and the behavior of the models changed during and after the financial crisis.

Last but not least Cinquegrana, G., & Sarno, D. (2010) tested the predictive power of the yield spreads for forecast the future growth of the real activities in the European Monetary Union using a multivariate version of the yield curve model using Vector Autoregressive Model. Their estimates confirm the significant relationship between the yield curve and GDP growth rate in monthly or quarterly frequency.

3. Theoretical Approach

A yield curve is a line that plots yields, interest rates of bonds having equal credit quality but differing maturity dates. The slope of the yield curve gives an idea of future interest rate changes and economic activity. There are three main types of yield curve shapes: normal (upward sloping curve), inverted (downward sloping curve) and flat. The yield curve is used as a benchmark for other debt in the market and it is used to predict changes in economic output and growth. The most frequently reported yield curve compares the three-month, two-year, five-year, 10-year and 30-year U.S. Treasury debt. A normal yield curve is one in which longer maturity bonds have a higher yield compared to shorter-term bonds due to the risks associated with time. An inverted yield curve is one in which the shorter-term yields are higher than the longer-term yields, which can be a sign of an upcoming recession. In a flat yield curve, the shorter - and longer-term yields are very close to each other, which is usually also a predictor of an economic transition for that reason many financial markers observe very carefully the yield curve's shape.

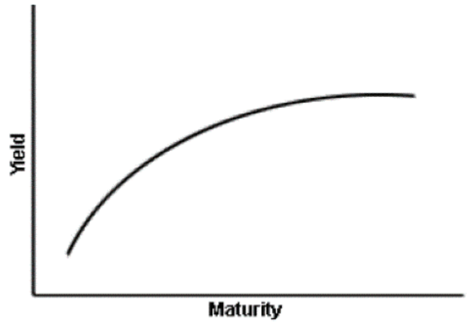
While the main goal of this research is the predictive power of the yield curve, forecasts of that type are based on strong theoretical footing. First we start with the expectation hypothesis. Under this theory, long-term interest rates are the average of expected future short-term rates. More generally, the expectations hypothesis equates the yield (at time t) on an n-period bond Y_{nt} and a sequence of time periods.

Another important aspect is the policy anticipations hypothesis. Bond yields are significantly affected by monetary policies changes from the actions of the Central Bank, a currency board or other committees. Central banks are well aware of their ability to influence the asset prices and use that to moderate oscillations of the economy. When policymakers reduce the short term interest rates due a recession period market participants who expect a recession also expect low interest. Another possibility is that the current monetary policy may shift both the yield curve and future output. Tight monetary policy might raise short term interest rates, flattening the yield curve and leading to slower future growth. On the other hand, easy policy could reduce short-term interest rates and stimulate future growth. In that sense yield curves reflects the direction of the future output by predicting future interest rates or future monetary policies.

Another assumption we could take into account is the fact that different bond investors prefer different maturity bonds with variable length and they are willing to buy other maturity bonds than their preference only if there is available a risk premium for the maturity length. This theory ,also known as liquidity preference theory, suggests that when all else is equal, investors prefer to hold short-term bonds in place of long-term bonds and that the yields on longer term bonds should be higher than shorter term bonds. The risk premium has additional information on its own, which is significant for the possible predictive power of the yield curve. Considering, for example, that a recession is approaching many people may feel uncertain about their future income and employment, or even about future interest rates. These explanations provide motivation for examining the predictive power of the yield curves and its consistency. In this research we will concentrate on the predictability on GDP growth and unemployment rate.

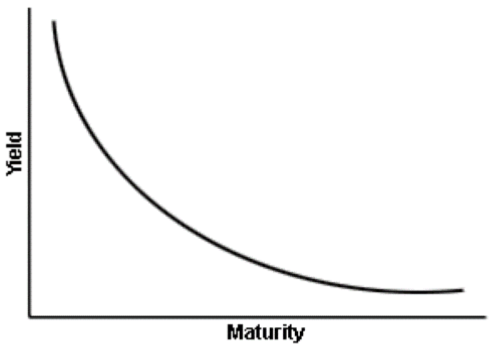
These are the 3 types of yield curves:

a) Normal Yield Curve



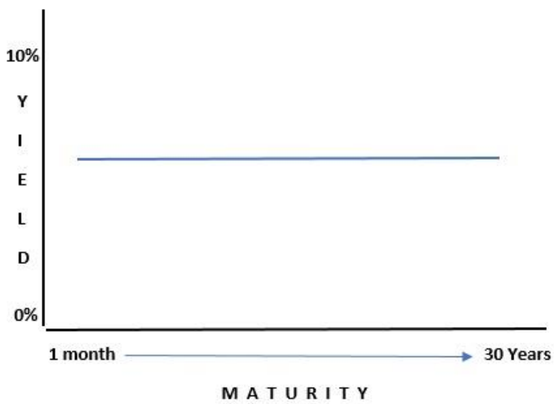
Source: The Balance.com

b) Inverted Yield Curve



Source: The Balance.com

c) Flat Yield Curve



Source: Theacademy.com

4. DATA

Before evaluating the forecasting of the yield curves several distinctions must be made regarding the variables that will be used. This section describes the data and criteria used to evaluate the predictive power of the yield curve. This research we examine the case of the G7 industrial countries towards their relation with the yield curve. These countries are Canada, Japan, France, Germany, Italy, United States and United Kingdom. For our examination we need the length of the variables to be at least 20 years, a criterion which has been ensured.

Another aspect is the yield curve itself. In testing the predictive power of the yield spread, it is important to choose the yields of debt securities which are actively traded and which reflect market expectations. Yield curve is the difference between interest rates on long-term and short-term security. But there are several bond and treasury securities that can justify this criterion and there are several alternative measures of the yield spread. For example some important interest rates monitored by market practitioners include the 3-month Treasury bill rate, 3-month interbank rate, 3-month certificate of deposit, the 1-year, 5-year, 10-year Treasury note rates; and the 30-year Treasury bond rate. Previous literature on the predictability of the spread suggests that the most balanced is the one with 10-year Treasury bond rate and the 3-month Treasury bill rate. Consequently when possible, the yield spread examined for each country is the spread between the rate on the 10-year government bond and the 3-month government bill rate. In countries where these assets are not traded another alternative asset must be used as Bonser-Neal, C., & Morley, T. R. (1997) are stating. So in our analysis for countries that the 3-month government bill is not available an alternative short term asset is used such as 3-month Interbank rates and 3-month certificates of deposit.

Next we have the variables of GDP growth for each country of G7 and Unemployment rate. GDP is only available on a quarterly basis but Unemployment rate is monthly. For that case we used both monthly frequency and quarterly and we will compare the results of both datasets. Our sample periods are for Canada and United States from 01/01/1973 to 01/08/2020. For Germany and Italy our sample consist from 01/01/1991 to 01/08/2020, for France 01/01/1983 to 01/08/2020, 01/04/1994 to 01/08/2020 for Japan and for United Kingdom 01/01/1973 to

01/06/2017. We concluded to use data after 1973 to avoid the intense fluctuations of on the exchange rates because of the Bretton Woods. For countries that our data start later periods it is due to data availability as well for United Kingdom, since we were not able to find data for the 3-month treasury security. For the quarterly data for Canada and United States our sample starts from 1st quarter of 1973 to 3rd quarter of 2020. For Germany and Italy 1st quarter 1991 to 3rd quarter of 2020, for France 1st quarter of 1983 to 3rd quarter of 2020, 2nd quarter of 1994 to 3rd quarter of 2020 and 1st quarter of 1973 to 2nd quarter of 2017 for United Kingdom.

The reasoning behind this, is to look at the differences in the results between the frequencies. In addition the monthly data can provide an even larger size. Moreover, we use the Industrial production rate as a leading economic index as well for testing the predictive power of the yield spread as well which is, as well as Unemployment rate, also available on a monthly basis. Lastly all data are from OECD, "Main Economic Indicators - complete database" via FRED economic database.

5. Methodology

Once the variables have been selected the next step is to choose the forecasting techniques we are going to use. Two types of forecasting techniques can
be employed to evaluate the forecast power of the yield spread: in-sample, out-of-sample forecasts and Vector Autoregression analysis and forecasting as well.

5.1 Forecasting basis

For each observation in the forecast sample, it is computed a fitted value of the dependent variable using the estimated parameters, the right-hand side exogenous variables, and either the actual or estimated values for lagged endogenous variables and residuals. The method of constructing these forecasted values depends upon the estimated model. In our case we start with a simple linear regression model with no lagged endogenous variables that are going to be subjoined later in the process. For every observation in the forecast period, will be computed the fitted value of Y using the estimated parameters and the corresponding values of the regressors:

$y_t = C(1) + C(2)x_t + C(3)Z_t$

As for the forecasts with lagged dependent variables in the form of $\mathrm{y\ c\ x\ z}(-1)$ there are unlike before the possibility for dynamic forecasting. The equation for computing the dynamic forecasting with the implemented lagged variable is:

$Y_s = C(1) + C(2)X_S + C(3)Z_S + C(4)y_{S-1}$,where y_{S-1} s the value of the lagged endogenous variable in the period prior to the start of the forecast sample.

The initial observation in the forecast sample uses the actual value of lagged Y. Thus, if the first observation in the forecast sample S is the first observation we have $y_s = C(1) + C(2)X_{S+N} + C(3)Z_{S+N} + C(4)\check{y}_{S+K-1}$.

The first observation uses the actual values of all three lags $y_{s-3}, y_{s-2}, y_{s-1}$. The second observations uses the actual values for y_{s-3} and y_{s-2} for the forecast forecasting value of the y_s of the first lag of y_{S-1}. The third observation will use in similar fashion the actual values for y_{S-1} and forecasting values of y_{S+1} and y_S for the first and second lag of y_{S+1}

It is important finally that in that type of forecasting is required that data for the exogenous variables is available for every observation in the forecast sample, and that values for any lagged dependent variables that are observed at the start of the forecast sample.

5.2 In-sample and out-of-sample forecasts

An in-sample forecast estimates the average relationship between the yield spread and the economic activity over the entire period for which data are available. Since it measures the average over the full period an in-sample forecast is calculated using information which was not available at the time market participants formed their forecast meaning that the forecast would be calculated based in the relationship between the two variables are based through all the periods of our sample. An out-of-sample on the other hand estimates the forecast based on the relationship between our variables only prior to our pointed year on the sample. Because both of those forecasts can provide us insight on the relationship and predictive ability of the yield curve we chose to use both of them. As for the length of the forecasts this research estimates the ability of the yield curve to predict GDP growth and Unemployment rate in one, two and three years to the future based on the previous researches of Estrella and Mishkin (1995) and Estrella and Hardouvelis (1991). Our forecasting equations are the following.

- Yield Spread In-Sample: GDP growth_t or $\text{Unemployment rate}_t = a + b\ \text{spread}_t$
- Yield Spread Out-of-Sample: GDP growth_t or $\text{Unemployment rate}_t = a + b\ \text{spread}_t$
- Lagged GDP growth and Lagged Unemployment rate:
  GDP growth_t or $\text{Unemployment rate}_t = a + b\ \text{GDP growth}_{t-n}$ or $a + b\ \text{Unemployment rate}_{t-n}$
- Lagged GDP growth and Lagged Unemployment plus the yield spread:
  GDP growth_t or $\text{Unemployment rate}_t = a + b\ \text{GDP growth}_{t-n} + c\ \text{spread}_t$ or $a + b\ \text{Unemployment rate}_{t-n} + \text{spread}_t$
- Industrial Production as a leading indicator =
  GDP growth_t or $\text{Unemployment rate}_t = a + b\ \text{Industrial production}_t$

Firstly we measure the initial Least square equations and progressively we apply the forecasts in any of the equations above in both monthly and quarterly frequency. It is important that when estimating this forecasting equation for n=1, 2, or 3 years with quarterly or monthly data causes the error term to be serially correlated. In that case, the standard errors from the estimation are corrected following HAC covariance method Newey and West (1987).

We will use the equations above so we can compare our results with the initial in and out-of-sample regression with the spread as the main variable. Following with a forecasting model which uses their own lagged values as explanatory variable and finally forecasting with another leading indicator of economic growth, in our case Industrial production, so we can compare the yield spread's results towards GDP growth and Unemployment rate. The evaluation method of the forecasts will be described below.

5.3 Forecast evaluation

Before we explain the forecast evaluation process it's important to clarify that forecasts are made with error, where the error is simply the difference between the actual and forecasted value. There are two sources of forecast error the residual uncertainty and coefficient uncertainty.

The first source of error, termed residual or innovation uncertainty arises because the error term e in the equation are unknown for the forecast period and are replaced with their predictions. While the residuals are zero in expected value, the individual values are non-zero; the larger the variation in the individual residuals, the greater the overall error in the forecasts. Residual uncertainty is usually the largest source of forecast error.

The second source of forecast error is coefficient uncertainty. The estimated coefficients f the equation deviate from the true coefficients
in a random fashion. The standard error of the estimated coefficient, given in the regression output, is a measure of the precision with which the estimated coefficients measure the true coefficients.

The effect of coefficient uncertainty depends upon the exogenous variables. Since the estimated coefficients are multiplied by the exogenous variables in the computation of forecasts, the more the exogenous variables deviate from their mean values, the greater is the forecast uncertainty.

Our main indicator for the evaluation of the forecast is the Root Mean Square Error. Root Mean Square Error (RMSE) is the standard deviation of the residuals (prediction errors). Residuals are a measure of how far from the regression line data points are; RMSE is a measure of how spread out these residuals are. In other words, it explains how concentrated the data is around the line of best fit. The equation is the following:

a) $\sqrt{\sum_{i=1}^{n} \frac{(\widehat{yi}- yi)^2}{n}}$

$\widehat{yi}$ is the predicted value, y_i is the observed value and n the number of observations.

It can also be decomposed as:

b) $\sum \frac{(\mathrm{yt}-\mathrm{yt})^2}{\mathrm{h}} = \left\{\left(\sum \frac{\widehat{y_t}}{\mathrm{h}}\right) - \bar{\mathrm{y}}\right\}^2 + \left(\mathrm{s_y} - \mathrm{s_y}\right)^2 + 2(1-\mathrm{r})\mathrm{s_y}\mathrm{s_y}$

where $\frac{(yt-yt)^2}{h}$, $\bar{y}$, s_y , s_y are the means and biased standard deviations of y_t is the correlation between $\hat{y}$ and y.

The Root Mean Squared Error statistic depends on the scale of the dependent variable. The smaller the error, the better the forecasting ability of that model according to that criterion.

5.4 Vector Autoreggresive analysis and Vector Error Correction

It's important, before we run the VAR or VECM model to test for stationarity of our variables and continuously to test for cointegration. In the case our variables are cointegrated that means we have to use the VAR restricted which is the vector error correction model (VECM) otherwise we use the normal VAR model.

5.4.1 Unit root tests

At this point firstly we center around the unit root tests to examine if our variables are stationary. First differencing is appropriate for I(1) time series and time-trend regression is appropriate for trend stationary I(0) time series. Unit root tests can be used to determine if trending data should be first differenced or regressed on deterministic functions of time to render the data stationary. Moreover, economic and finance theory often suggests the existence of long-run equilibrium relationships among non stationary time series variables. If these variables are I(1), then cointegration techniques can be used to model these long-run relations. Kwiatkowski, Phillips, Schmidt and Shinn (1992). Hence, pre-testing for unit roots is often a first step in cointegration modeling. The econometric issues associated with unit root and stationarity tests, consider the stylized trend-cycle decomposition of a time series y_t

$y_t = T\,D_t + z_t$

$T\,D_t = \kappa + \delta_t$

$z_t = \varphi zt - 1 + \varepsilon t,\ \varepsilon t \sim W\,N(0, \sigma 2)$

Where TDt is a deterministic linear trend and zt is an auto regressing process. If $|\varphi| < 1$ then yt is I(0) about the deterministic trend T Dt. If $\varphi = 1$, then $z_t = z_{t-1} + \varepsilon_t = z_t + \sum_{j=1}^{t} \varepsilon_j$, a stochastic trend and y_t is I(1) with drift. Autoregressive unit root tests are based on testing the null hypothesis that $\varphi = 1$ (difference stationary) against the alternative hypothesis that $\varphi < 1$ (trend stationary). They are called unit root tests because under the null hypothesis the autoregressive polynomial of z_t, $\varphi(z) = (1 - \varphi z) = 0$, has a root equal to unity

Unit root test with constant only

When testing for unit roots, it is crucial to specify the null and alternative hypotheses appropriately to characterize the trend properties of the data at hand. The trend properties of the data under the alternative hypothesis will determine the form of the test regression used. Furthermore, the type of deterministic terms in the test regression will influence the asymptotic distributions of the unit root test statistics.
The test regression for constant only unit root test is:

$y_t = c + \varphi y_{t-1} + \varepsilon_t$

and includes a constant to capture the nonzero mean under the alternative.
The hypotheses to be tested are

H0 : $\varphi = 1 \Rightarrow y_t \sim I(1)$ without drift

H1 : $|\varphi| < 1 \Rightarrow y_t \sim I(0)$ with non-zero mean

This formulation is appropriate for non-trending financial series like interest rates, exchange rates, and spreads like the yield spread we are using in this research.

Unit root tests with constant and trend

The test regression in this case is $y_t = c + \delta_t + \varphi y_{t-1} + \varepsilon_t$
Includes a constant and deterministic time trend to capture the deterministic trend under the alternative. The hypotheses to be tested are

H0 : $\varphi = 1 \Rightarrow yt \sim I(1)$ with drift

H1 : $|\varphi| < 1 \Rightarrow yt \sim I(0)$ with deterministic time trend

This formulation is appropriate for trending time series like asset prices or
the levels of macroeconomic aggregates like real GDP and Unemployment rate.

Augmented Dickey Fuller

The ADF test tests the null hypothesis that a time series yt is I(1) against the alternative that it is I(0). The regression which is based is:

$$y_t = \beta' D_t + \varphi y_{t-1} + \sum_{j=1}^{p} \psi_j \, \Delta y_{t-j} + e_t$$

D_r is a vector of deterministic terms (constant, trend etc.). The p refers to the lagged difference terms, Δy_{t-1} , are used to approximate the structure of the errors, and the value of p is set so that the error ε_t is serially uncorrelated. The error term is also assumed to be homoskedastic. The specification of the deterministic terms depends on the assumed behavior of y_t under the alternative hypothesis of trend stationarity. Under the null hypothesis, y_t is I(1) which implies that $\varphi = 1$.

An important parametric issue for the implementation of the ADF test is the specification of the lag length p. If p is too small then the remaining serial
correlation in the errors will bias the test. According to the literature If the absolute value of the t-statistic for testing the significance of the last lagged difference is greater than 1.6 then set $p = p_{max}$ and perform the unit root test. Otherwise, reduce the lag length by one and repeat the process.

5.4.2 Johansen Cointegration test

To use Johansen's method, we need to turn the VAR of the form

$$\underset{g\times 1}{y_t} = \underset{g\times g}{\beta_1}\ \underset{g\times 1}{y_{t-1}} + \underset{g\times g}{\beta_2}\ \underset{g\times 1}{y_{t-2}} + \ldots + \underset{g\times g}{\beta_k}\ \underset{g\times 1}{y_{t-k}} + \underset{g\times 1}{u_t}$$

into a VECM, which can be written as:

$$\Delta y_t = \Pi\, y_{t\text{-k}} + \Gamma_1\, \Delta y_{t-1} + \Gamma_2\, \Delta y_{t-2} + \ldots + \Gamma_{k-1}\, \Delta y_{t-(k-1)} + u_t$$

This test requires to specify the lag order and parameters to be specified. To solve this we apply the Vector Autoregressive for the specification of the lag order. In this method the Null Hypothesis is that there is no co-integration and it is rejected at the point where the Max and Trace statistics are above 5%. In addition the equation of this procedure will show us if there is a strong or not relation, which depends on the degree of the relation between the variables as it will be shown by the equation.

5.4.3 Impulse responses

Since all variables in a VAR model depend on each other, individual coefficient estimates only provide limited information on the reaction of the system to a shock. In order to get a better picture of the model's dynamic behavior, impulse responses are used. The departure point of every impulse response function for a linear VAR model is its moving average representation, which is also the forecast error impulse response function

$$\varphi_i = \sum_{j=1}^{i} \varphi_{i-j} A_j, \quad i = 1,2 \ldots n$$

with $\Phi_0 = I_K$ and $A_J = 0$ for $j > p$, where K is the number of endogenous variables and p is the lag order of the VAR model.

Impulse response analysis is an important step in econometric analyses, which employ vector autoregressive models. Their main purpose is to describe the evolution of a model's variables in reaction to a shock in one or more variables. This feature allows to trace the transmission of a single shock within an otherwise noisy system of equations and, thus, makes them very useful tools in the assessment of economic policies

The next section is the results of the research.

6. Results

6.1 Unit Root tests

For our analysis we conducted the ADF unit root test. For all G7 countries the variables of GDP growth and Yield spread proved to be stationary with P-Value close to 0 and Unemployment rate proved to be non stationary variable with the exception of United States where we could not reject the null hypothesis that it is not stationary. All the tests are available at the Appendix.

6.2 Yield Spread and Leading Indicator In-Sample and Out-Of-Sample

In this section we present the outcome of the research, showing the predictive power of the yield curve on the G7 industrial countries. First the in-sample and out-of sample, continuously the dynamic forecasting on the lagged regressions and lastly the VAR analysis. The results, as mentioned before, are deliberated both monthly and quarterly. The initial procedure for our model was to create the starter Least square equation in which the dependent variable is GDP growth or Unemployment rate and the other one the yield spread. After that are forecast In-Sample for the last 1, 2 and 3 years. In every sample we forecast the last 3 years meaning 2017 to 2020 in the sequence we described earlier. This does not apply to U.K. because our sample is up to 2017, so we use the sequence on the same manner for 2014 to 2017. For the out-of Sample we run another least square model up to 2017 either monthly or quarterly. Again the exception is U.K. which we run the same sample up to first month or quarter of 2014. Then we proceed to Out-of-Sample forecasts for 1,2 and 3 years meaning for 2018, 2019 and 2020 or for United Kingdom 2015, 2016 and 2017. Another important note is that the out-of-sample forecasts in monthly frequency are applied at month second month and quarterly at the second quarter. This causes some implications for the quarterly data because of the Covid-19 crisis that started at the end of February of 2020.

In the first tables it's the Root Mean Squared Errors of the In-Sample and Out-Of-Sample forecasting methods for the yield spread and leading indicator equations:

GDP Growth	Yield Spread : In-Sample			Yield Spread : Out-Of-Sample		
	1 year	2 years	3 Years	1 Year	2 years	3 Years
Canada	0,26	0,23	0,55	0,21	0,22	1,06
France	0,27	0,22	0,3	0,24	0,15	1,98
Germany	0,55	0,44	0,59	0,54	0,44	0,6
Italy	0,34	0,25	1,79	0,28	0,21	1,8
Japan	0,58	0,58	0,8	0,49	0,5	0,8
UK	0,07	0,11	0,12	0,08	0,11	0,12
US	0,26	0,21	0,8	0,23	0,18	0,81

Table 1: Root Mean Squared Errors in the basis of 1,2 and 3 years forecasting for GDP growth with yield spread monthly frequency

Unemployment Rate	In-Sample			Out-of-sample		
	1st Year	2nd year	3rd Year	1st Year	2nd year	3rd Year
Canada	1,85	1,97	1,99	1,95	2,07	2,1
France	0,54	0,75	1,05	0,66	0,87	1,17
Germany	3,28	3,47	3,46	3,72	3,91	3,93
Italy	1,33	1,05	0,87	1,43	1,15	0,95
Japan	0,87	1,03	1,09	1,54	1,69	1,78
UK	1,13	1,53	1,83	0,35	1,02	1,44
US	1,79	1,84	1,78	1,87	1,93	1,88

Table 2: Root Mean Squared Errors in the basis of 1,2 and 3 years forecasting for Unemployment Rate ,monthly frequency

GDP Growth	In-Sample			Out-of-sample		
	1 year	2 year	3 year	1 year	2 year	3 year
Canada	0,33	0,28	1,05	0,24	0,2	4,32
France	0,56	0,54	2,89	0,39	0,46	2,9
Germany	0,42	0,71	4,31	0,13	0,11	3,97
Italy	0,56	0,44	1,7	0,37	0,27	1,79
Japan	0,39	0,43	0,8	0,36	0,42	0,85
UK	0,18	0,23	0,74	0,19	0,25	0,76
US	0,29	0,24	0,4	0,26	0,2	0,82

Table 3: Root Mean Squared Errors in the basis of 1,2 and 3 years forecasting for GDP Growth with leading indicator: Industrial Production. monthly frequency

Unemployment Rate	In-Sample			Out-of-sample		
	1 year	2 year	3 year	1 year	2 year	3 year
Canada	0,81	0,92	1,04	0,96	1,08	1,2
France	0,27	0,48	0,82	0,35	0,56	0,9
Germany	2,1	2,26	2,52	2,1	2,26	2,52
Italy	1,04	0,82	0,76	0,89	0,7	0,72
Japan	1,22	1,37	1,46	1,44	1,59	1,69
UK	1	1,37	1,6	1,16	1,53	1,8
US	1,2	1,35	1,49	1,4	1,56	1,7

Table 4: Root Mean Squared Errors in the basis of 1,2 and 3 years forecasting for Unemployment Rate with leading indicator: Industrial Production, monthly frequency

For GDP growth with monthly data the yield spread gives similar predictions with Industrial production with both having significantly low Root Mean Squared Error in the first and second year but the yield spread being more consistent for the 3rd year as well even if it loses some of its power. Out-of-sample forecasting works better in most cases and give us slightly more accurate predictions in both models. The leading indicator model produces better results only in the cases of Germany and United States. One possible reason for this outcome can be the heavy industrialization of both countries that make the industrial production a variable of high significance for the GDP growth.

In the case of Unemployment rate both models generate poor results with the yield spread being slightly better. In both cases France has optimal results with the second model being superior and Germany has the worse prediction with the second model performing better as well. In this case the In-Sample method gives us lower squared errors with the exception of Japan.

For the quarterly data we have:

GDP Growth	In-Sample			Out-of-sample		
	1st year	2nd year	3rd year	1st year	2nd year	3rd year
Canada	0,26	0,3	3.36	0,24	0,2	4,32
France	0,56	0,54	2,89	0,39	0,46	2,9
Germany	0,42	0,71	4,31	0,47	0,48	3,97
Italy	0,28	0,22	3,97	0,26	0,2	3,98
Japan	0,49	0,58	2,32	0,42	0,53	2,36
UK	0,09	0,15	0,16	0,09	0,14	0.16
US	0,21	0,2	2.71	0,19	0,22	2,74

Table 5: Root Mean Squared Errors in the basis of 1,2 and 3 years forecasting for GDP growth, quarterly frequency, yield spread equation

Unemployment Rate	In-Sample			Out-of-sample		
	1 year	2 years	3 years	1 year	2 years	3 years
Canada	1,38	1,42	2,05	1,41	1,45	2,07
France	0,62	0,87	1,3	0,74	0,96	1,43
Germany	3,4	3,46	3,3	3,87	3,96	3,83
Italy	1,22	0,93	0,86	1,29	1	0,9
Japan	0,92	1,05	1,07	1,6	1,7	1,74
UK	0,68	1,1	2,38	0,33	0,64	2,32
US	1,6	1,53	2,58	1,95	1,98	2,73

Table 6: Root Mean Squared Errors in the basis of 1,2 and 3 years forecasting for Unemployment Rate, quarterly frequency, yield spread equation

GDP Growth	In-Sample			Out-of-sample		
	1 year	2 year	3 year	1 year	2 year	3 year
Canada	0,35	0,39	3,35	0,24	0,2	4,32
France	0,56	0,54	2,89	0,39	0,46	2,9
Germany	0,42	0,71	4,31	0,39	0.52	2.91
Italy	0,47	0,4	3,51	0,32	0,25	3,78
Japan	0,35	0,48	2,14	0,35	0,48	2,3
UK	0,08	0,12	0.17	0,08	0,16	0,17
US	0,28	0,23	2,7	0,26	0,22	2,71

Table 7: Root Mean Squared Errors in the basis of 1,2 and 3 years forecasting for GDP growth, quarterly frequency, leading indicator equation

Unemployment Rate	In-Sample			Out-of-sample		
	1 year	2 years	3 years	1 year	2 years	3 years
Canada	1,96	2,15	2,52	2,31	2,5	2,77
France	0,34	0,58	1,38	0,43	0,67	1,47
Germany	1,21	1,51	1,98	2,06	2,32	2,64
Italy	0,93	0,71	1,3	0,8	0,61	1,43
Japan	0,68	1,1	2,38	0,33	0,64	2,32
UK	1,17	1,52	1,78	1,33	1,68	1,94
US	1,31	1,44	2,47	1,48	1,62	2,55

Table 8: Root Mean Squared Errors in the basis of 1,2 and 3 years forecasting for Unemployment Rate, quarterly frequency, leading indicator equation

On quarterly basis, as well as, monthly basis the results for both equations are almost identical with again the out-of-sample forecasting performing slightly better. The difference in this frequency is that the lowest Root Mean Squared Error is at the 1 year forecast and it gets weaker in the 2 year. As we can see in both models in the 3 year prediction rises largely. The cause for this is the start of the pandemic of COVID-19 that disrupted the world economy in February of 2020. On the one hand the COVID-19 crisis triggered sharp falls in the prices of investment-grade corporate bonds, proportionately more than for high-yield bonds, which was surprising as high-yield bonds are riskier, less liquid, and more sensitive to a deterioration in the economic outlook, on the other hand affected the various industry groups as well in a drastic and severe between February and April 2020.

For the Unemployment Rate on quarterly basis in most cases the results are poorer than the GDP growth for the yield spread equation as well with the exception of

France and the United Kingdom. The indicator of Industrial production gives us similar results with the yield spread except Japan and France. With Japan having a solid Root Mean Squared error only at the 1 year forecasting. The forecasts lose their power after the 1 year prediction as well, with the 3 year prediction rising largely as well for the reasons we described above.

6.3 Lagged GDP growth and Unemployment rate

In this subsection we proceed regressing our initial models with their own lagged differences creating a dynamic forecasting and we will compare them to the results of the models above. In this case they are both monthly and quarterly basis as well.

	Lagged GDP growth			Lagged GDP plus spread		
Canada	0,28	0,26	0,6	0,26	0,23	1,04
France	0,56	0,54	2,89	0,42	0,71	4,31
Germany	0,56	0,45	0,61	0,6	0,48	0,57
Italy	0,18	0,23	1,78	0,37	0,28	1,19
Japan	0,37	0,42	0,83	0,59	0,57	0,8
UK	0,10	0.12	0.13	0,07	0,11	0,12
US	0,21	0,18	0,42	0,25	0,21	0,38

Table 9: Root Mean Squared Errors in the basis of 1,2 and 3 years forecasting for Unemployment Rate, quarterly frequency, Lagged GDP and Lagged GDP plus spread, monthly frequency

	Lagged Unemployment Rate			Lagged Unemployment Rate plus spread		
Canada	1	0,92	1,6	0,86	1,11	1,25
France	0,65	0,83	1,09	0,66	0,84	1,09
Germany	0,48	0,68	0,84	0,5	0,72	0,87
Italy	0,33	0,55	0,87	0,4	0,83	1,18
Japan	0,47	0,66	0,78	0,32	0,44	0,48
Uk	1,48	1,88	2,18	1,61	2,03	2,33
Us	1,01	1,38	1,67	1,05	1,36	1,52

Table 10: Root Mean Squared Errors in the basis of 1,2 and 3 years forecasting for Unemployment Rate, quarterly frequency, Lagged Unemployment Rate and Lagged Unemployment plus spread, monthly frequency

As for the quarterly frequency:

	Lagged GDP			Lagged GDP plus spread		
Canada	0,3	0,34	0,8	0,32	0,32	0,74
France	0,56	0,54	2,89	0,42	0,71	4,31
Germany	0,6	0,5	2,89	0,63	0,53	2,81
Italy	0,18	0,23	2,74	0,39	0,3	1,59
Japan	0,33	0,47	2,41	0,47	0,57	2,34
UK	0,12	0.17	0.16	0,12	0,17	0,16
US	0,21	0,19	2,72	0,24	0,21	2,68

Table 11: Root Mean Squared Errors in the basis of 1,2 and 3 years forecasting for Unemployment Rate, quarterly frequency, Lagged GDP and Lagged GDP plus spread, quarterly frequency

	Lagged Unemployment Rate			Lagged Unemployment Rate plus spread		
Canada	0,96	1,15	1,25	0,97	1,15	1,21
France	0,68	0,87	1,19	0,69	0,88	1,18
Germany	0,56	0,75	0,86	0,6	0,79	0,88
Italy	0,31	0,55	0,96	0,43	0,86	1,28
Japan	0,52	0,65	0,71	0,35	0,41	0,42
UK	1,6	1,95	2,24	1,74	2,1	2,39
US	1,1	1,46	1,72	1,17	1,41	1,53

Table 12: Root Mean Squared Errors in the basis of 1,2 and 3 years forecasting for Unemployment Rate, quarterly frequency, Lagged Unemployment Rate and Lagged Unemployment rate plus spread, quarterly frequency

In these models we can see that in both cases the model with their own lagged differences performs mostly better. For GDP growth France, Canada has a lower RMSE when we add the yield spread and for the United Kingdom is identical. As for unemployment rate its own lag seems more valid for predictions in both frequencies with the exception of Canada and Japan. The reason behind these differences may be the different structure and special characteristics of each country. Again the forecasts in any case lose predicting power after expansion for an extra year.

Model with lowest RMSE for each G7 country - monthly			
GDP growth	**1 year**	**2 years**	**3 years**
Canada	Spread Out-of-Sample	Leading indicator Out-of-Sample	Spread In-Sample
France	Spread Out-of-Sample	Spread Out-of-Sample	Spread In-Sample
Germany	Leading Indicator Out-of-Sample	Leading Indicator Out-of-Sample	Lagged GDP + Spread
Italy	Lagged GDP	Spread Out-of-sample	Lagged GDP + Spread
Japan	Leading Indicator out-of-sample	Leading Indicator out-of-sample	Spread Out-of-sample
U.K.	Spread In-Sample	Spread Out-of-Sample	Spread Out-of-Sample
U.S.	Lagged GDP	Lagged GDP	Lagged GDP + Spread

Model with lowest RMSE for each G7 country - quarterly			
GDP growth	1 year	2 years	3 years
Canada	Spread Out-of-Sample	Spread Out-of-Sample	Lagged GDP + Spread
France	Leading Indicator In-Sample	Leading Indicator Out-of-Sample	Spread In-Sample
Germany	Spread Out-of-Sample	Spread Out-of-Sample	Lagged GDP + Spread
Italy	Lagged GDP	Spread Out-of-Sample	Lagged GDP + Spread
Japan	Lagged GDP	Lagged GDP	Leading Indicator In- Sample
U.K.	Leading Indicator Out-of-Sample	Leading Indicator In-Sample	Lagged GDP + Spread
U.S.	Spread Out-of-Sample	Lagged GDP	Lagged GDP + Spread

Model with lowest RMSE for each G7 country - monthly			
Unemoloyment Rate	1 year	2 years	3 years
Canada	Leading Indicator In-Sample	Lagged Unemployment rate	Leading Indicator In-sample
France	Leading Indicator In-Sample	Leading Indicator In-Sample	Leading Indicator In-Sample
Germany	Lagged Unemployment rate	Lagged Unemployment rate	Lagged Unemployment rate
Italy	Lagged Unemployment rate	Lagged Unemployment rate	Lagged Unemployment rate
Japan	Lagged Unemployment rate + Spread	Lagged Unemployment rate + Spread	Lagged Unemployment rate + Spread
U.K.	Spread Out-of-Sample	Spread Out-of-Sample	Spread Out-of-Sample
U.S.	Lagged Unemployment rate	Leading Indicator In-Sample	Lagged Unemployment rate + Spread

Model with lowest RMSE for each G7 country - quarterly			
Unemployment Rate	1 year	2 years	3 years
Canada	Lagged Unemployment rate	Lagged Unemployment rate	Lagged Unemployment rate + Spread
France	Leading Indicator In-Sample	Leading Indicator In-Sample	Lagged Unemployment rate + Spread
Germany	Lagged Unemployment rate	Lagged Unemployment rate	Lagged Unemployment rate
Italy	Lagged Unemployment rate	Lagged Unemployment rate	Lagged Unemployment rate
Japan	Leading Indicator Out-of-Sample	Lagged Unemployment rate + Spread	Lagged Unemployment rate + Spread
U.K.	Spread Out-of-Sample	Spread Out-of-Sample	Leading Indicator In-Sample
U.S.	Lagged Unemployment rate	Lagged Unemployment rate + Spread	Lagged Unemployment rate + Spread

In conclusion as we can see in the tables above for the GDP growth the yield curve can show as staple prediction especially with the out-of-sample forecasting method along with its own lagged difference plus the yield spread. In-sample forecasting can give us some insight as well and has relatively low RMSE but it's not always a reliable indicator because it takes into account all past years of the sample.

As for the Unemployment rate the yield curve does not present us with the results we hoped. The best possible predictor for most of the G7 countries is their lagged difference and in some cases their lagged difference along with yield spread.

6.4 Vector Auto regression analysis

For the VAR analysis one of the first things we had to make clear is the number of lag intervals we ought to use. Too many lags can be the cause for the loss of degrees of freedom and in addition can cause multicollinearity, serial correlation in the error terms and misspecification errors. Usually for annually data the number of lags is typically small, 1 or 2, for quarterly data 1-8 and for monthly 6 or12 can give usually sufficient results. (Ivanov, V., & Kilian, L. (2005).

In our case we initially run the VAR model with 12 lags for monthly and 4 at quarterly. Then we use the function of lag length criteria to choose the optimal lag for each model. It computes various criteria to select the lag order of an unrestricted VAR and it is carried out as follows: $\mathrm{LR} = (\mathrm{T} - \mathrm{m})\{\log|\sum_{e,l-1}| - |\sum_{e,1}|\} \sim x^2(k^2)$
where m is the number of parameters per equation under the alternative, (T - m) is a sample modification, *k* is the number of endogenous variables and x is the output displays. We use the Akaike Information Criterion as our leading indicator. The following table shows us the number of lags that we used in each model for every G7 country:

Table 13: Lag length selection

AIC	Frequency	Number of lags for GDP growth model	Number of lags for Unemployment Rate model
Canada	Monthly	11	9
	quarterly	2	3
France	Monthly	12	9
	quarterly	3	3
Germany	Monthly	11	4
	quarterly	2	2
Italy	Monthly	11	12
	quarterly	3	3
Japan	Monthly	11	5
	quarterly	1	2
U.K.	Monthly	11	6
	quarterly	8	2
U.S.	Monthly	12	7
	quarterly	5	4

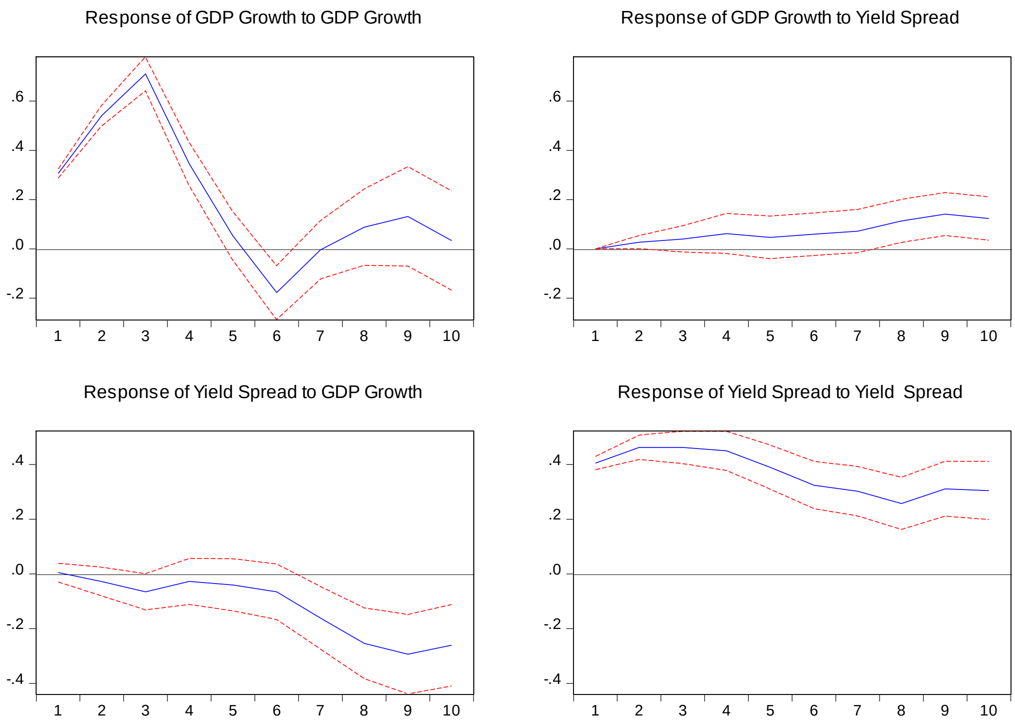
All stationarity tests and Johansen Cointegration tests are available at the Appendix. At the next sections we present the impulse responses and for each of the G7 countries

6.3.1 Impulse responses

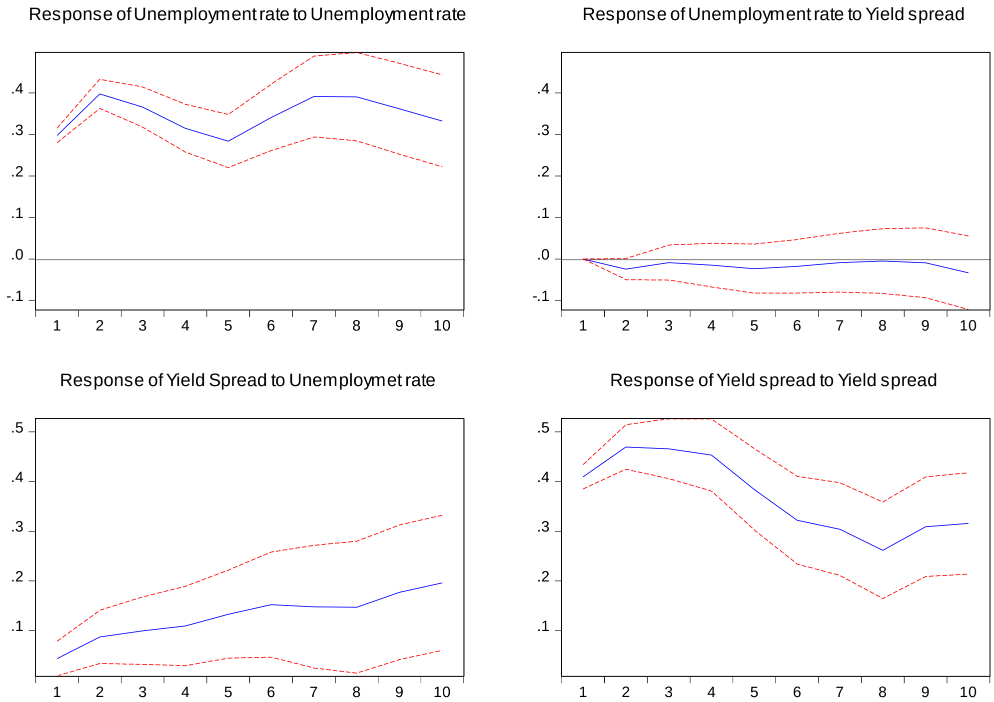
Firstly the monthly frequency for each country:

a) Canada

<u>GDP growth VAR model</u>

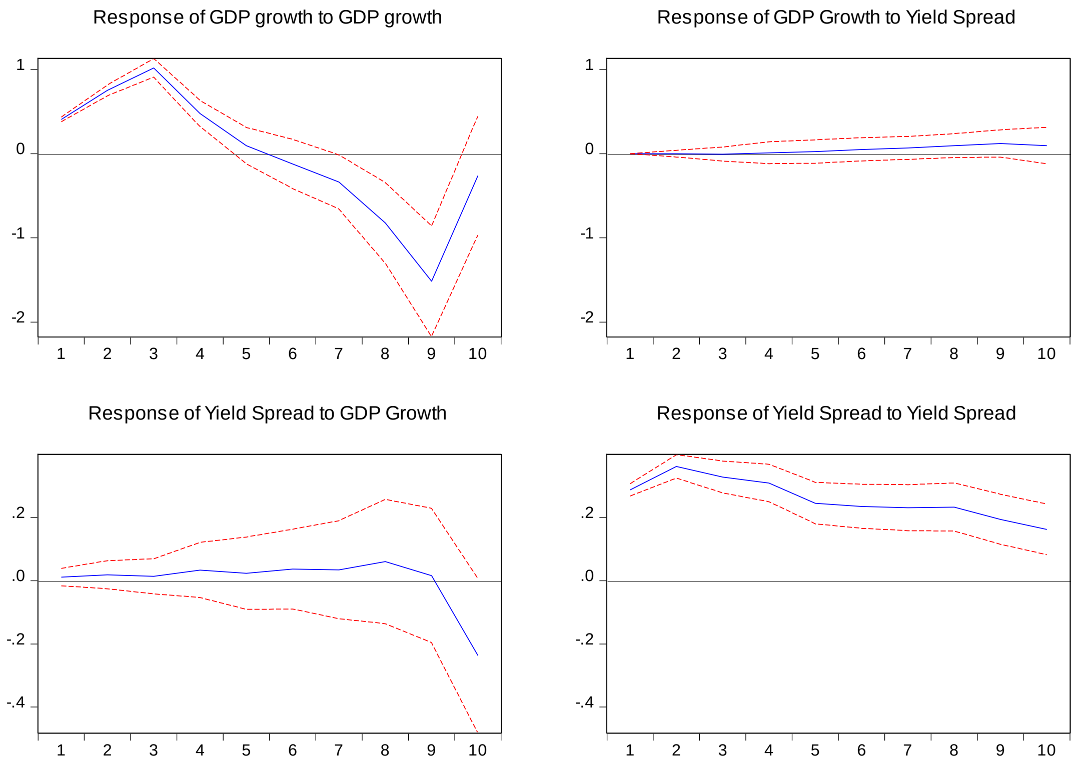


<u>Unemployment rate VAR model</u>

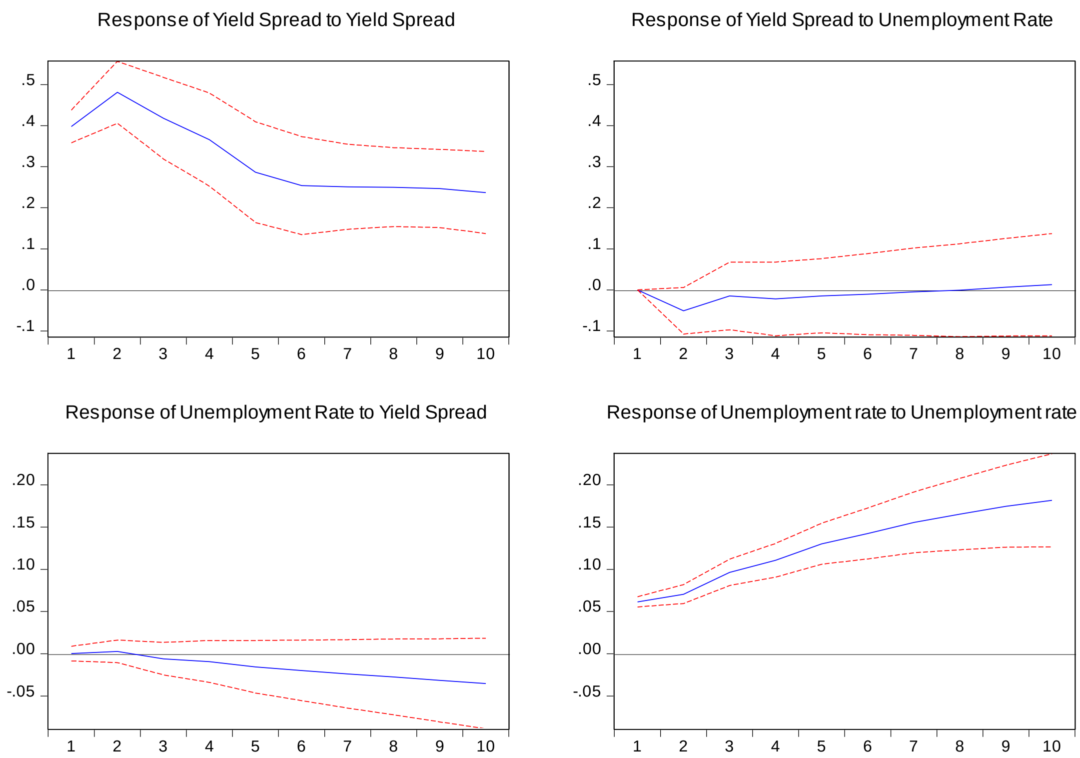


b) France

GDP growth VAR model

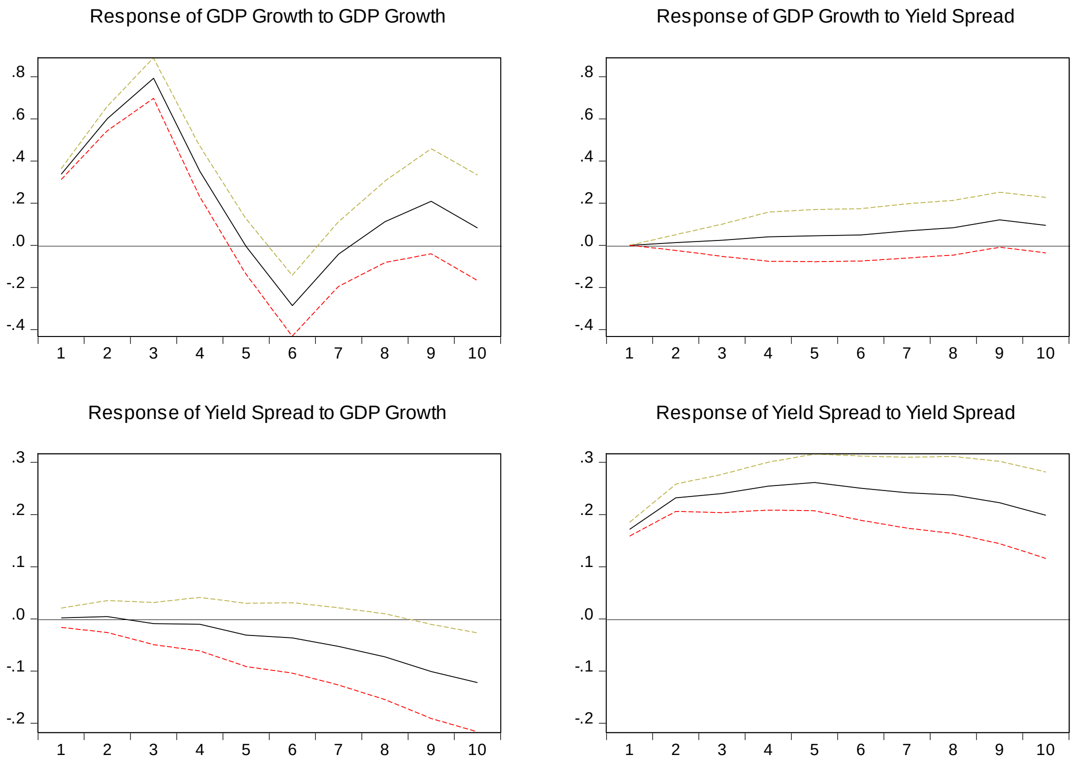


Unemployment rate VAR model

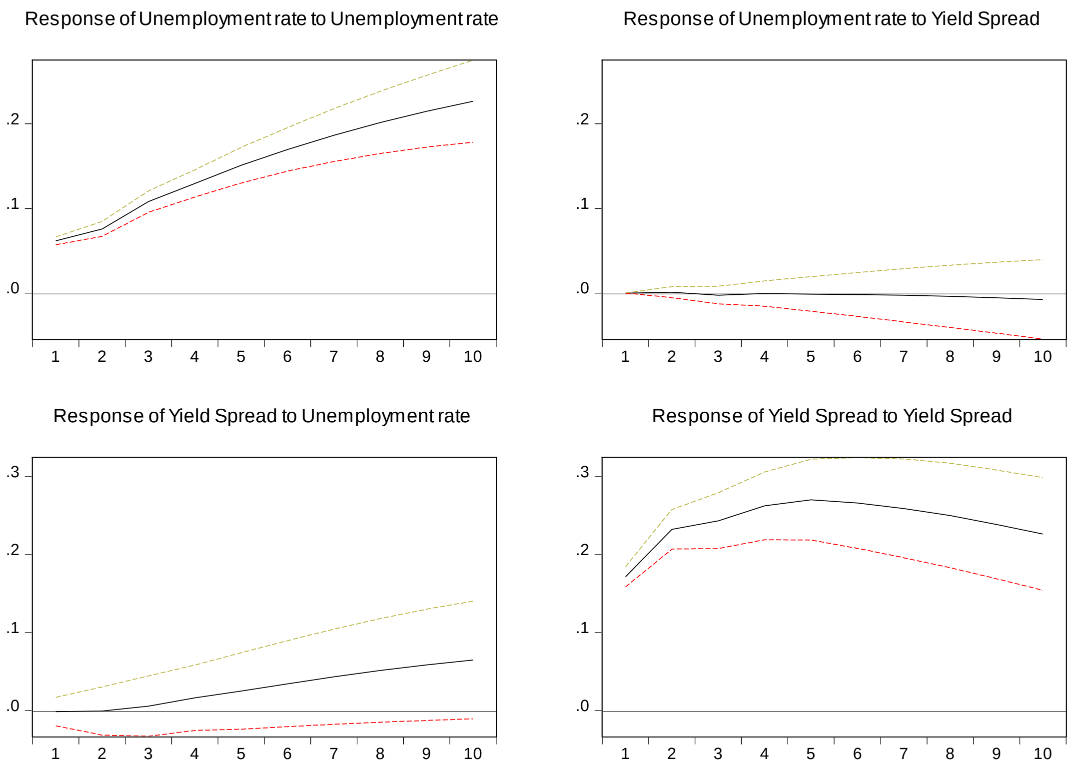


c) Germany

GDP growth VAR model

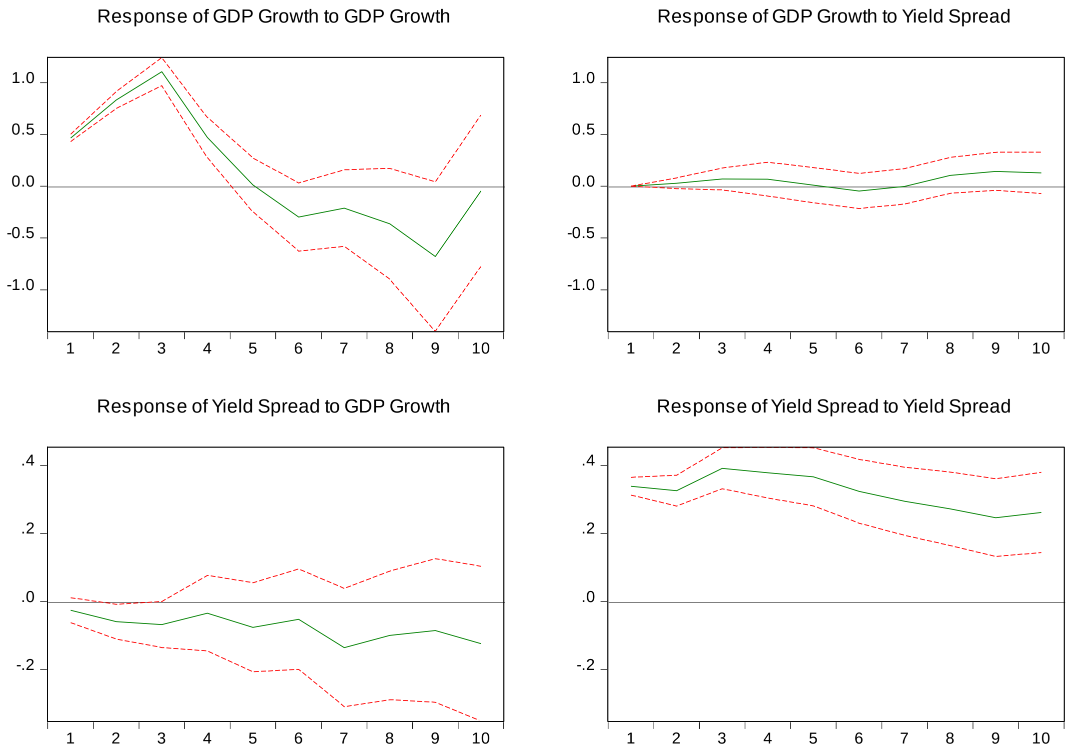


Unemployment rate VAR model

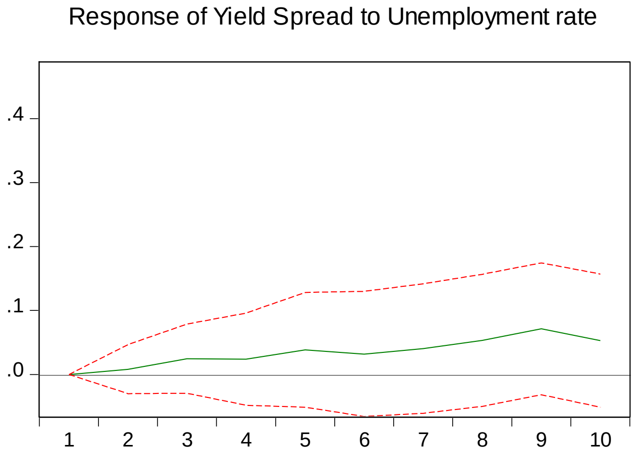


d) Italy

GDP growth VAR model



Unemployment rate VAR model


Response of Yield Spread to Unemployment rate
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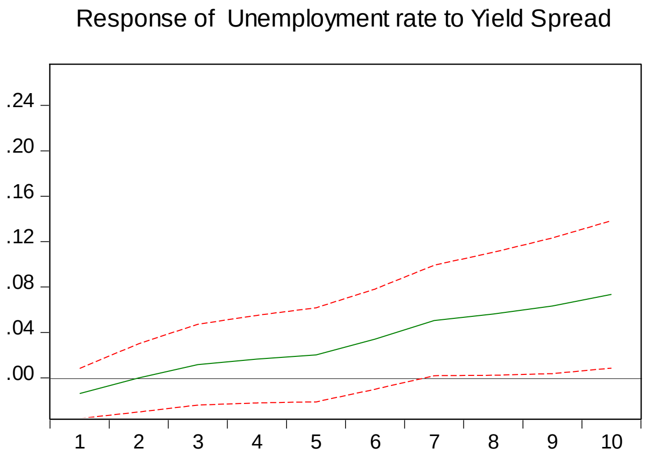
.3
.2
.1
.0
1
2
3
4
5
6
7
8
9
10


Response of Unemployment rate to Yield Spread
.24
.20
.16
.12
.08
.04
.00
1
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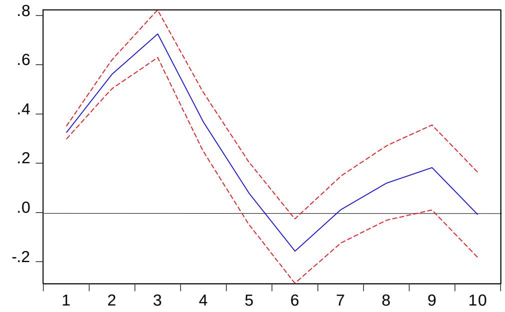
5
6
7
8
9
10

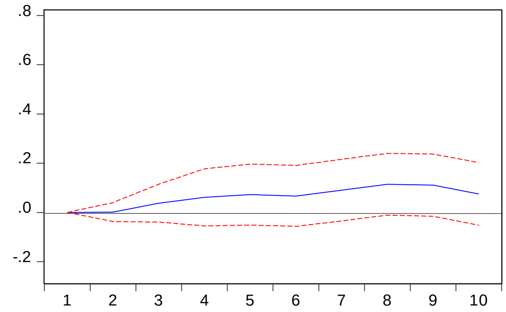
e) Japan

GDP growth VAR model

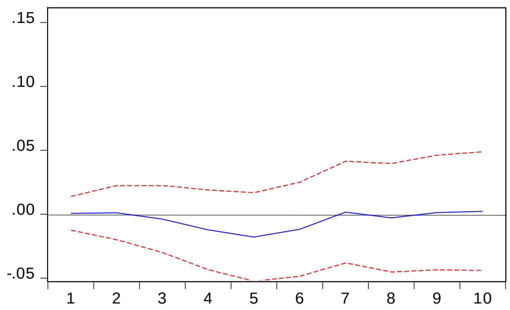
Response of GDP Growth to GDP Growth



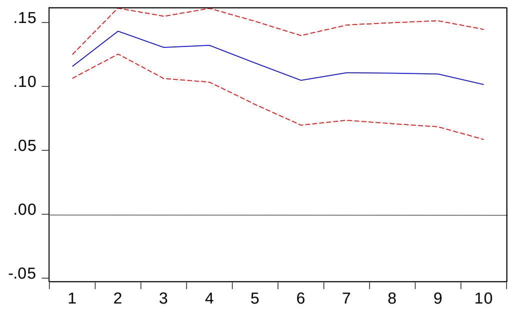
Response of GDP Growth to Yield Spread



Response of Yield Spread to GDP Growth

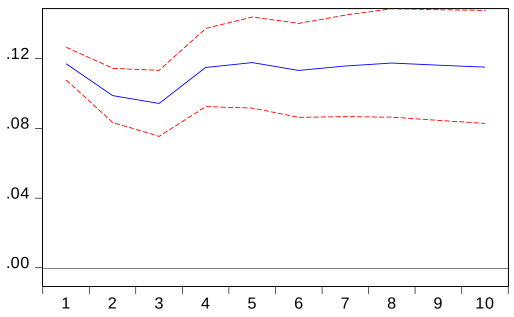


Response of Yield Spread to Yield Spread

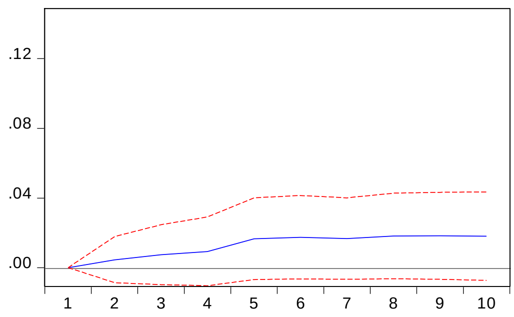


Unemployment rate VAR model

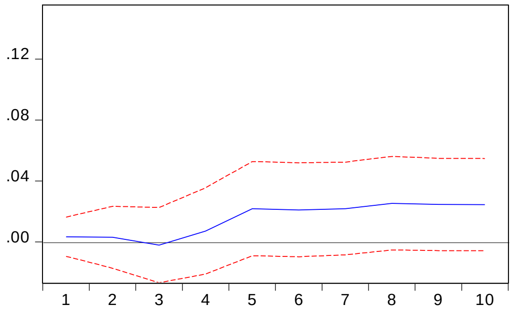
Response of Unemployment rate to Unemployment rate



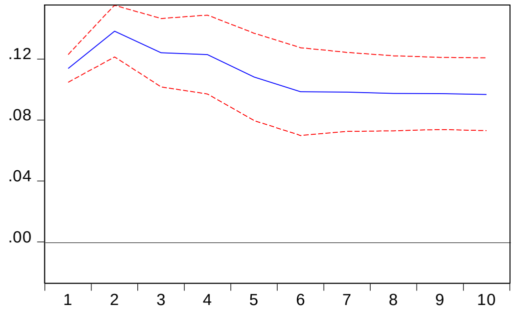
Response of Unemployment rate to Yield Spread



Response of Yield Spread to Unemployment rate



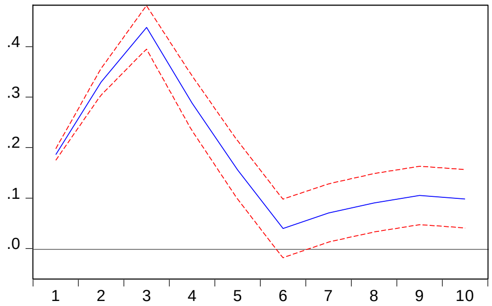
Response of Yield Spread to Yield Spread



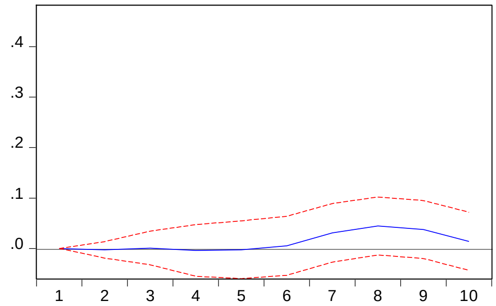
f) United Kingdom

GDP growth VAR model

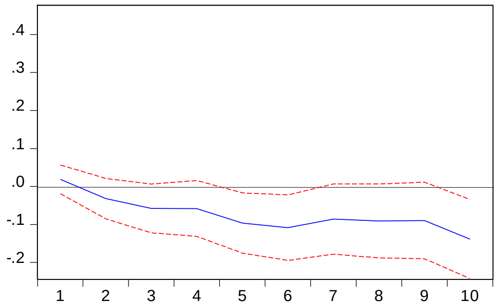
Response of GDP growth to GDP growth



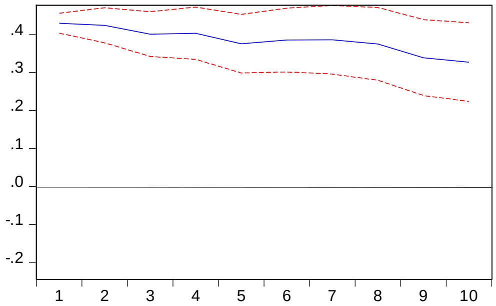
Response of GDP growth to Yield Spread



Response of Yield Spread to GDP growth

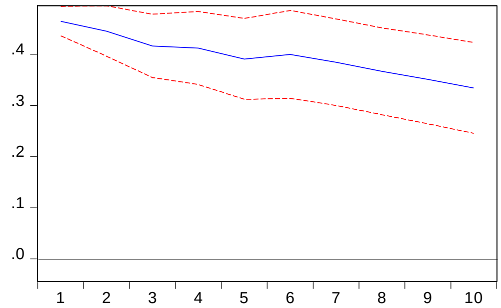


Response of Yield Spread to Yield Spread

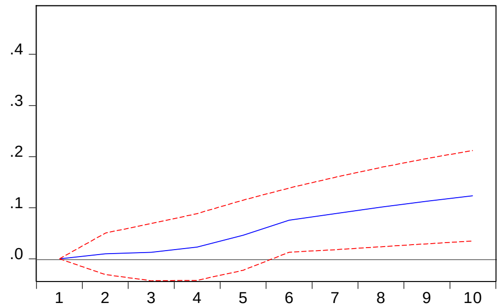


Unemployment rate VAR model

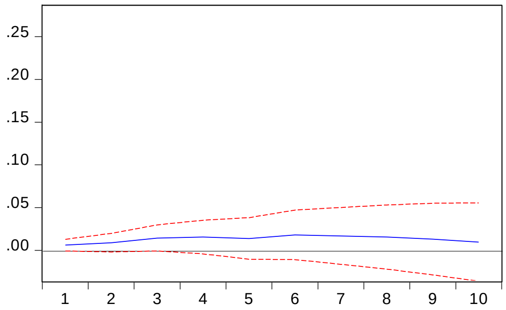
Response of Yield Spread to Yield Spread



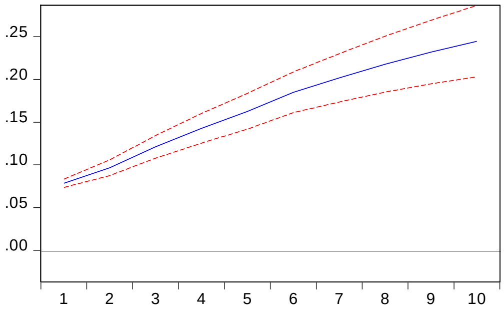
Response of Yield Spread to Unemployment rate



Response of Unemployment rate to Yield Spread

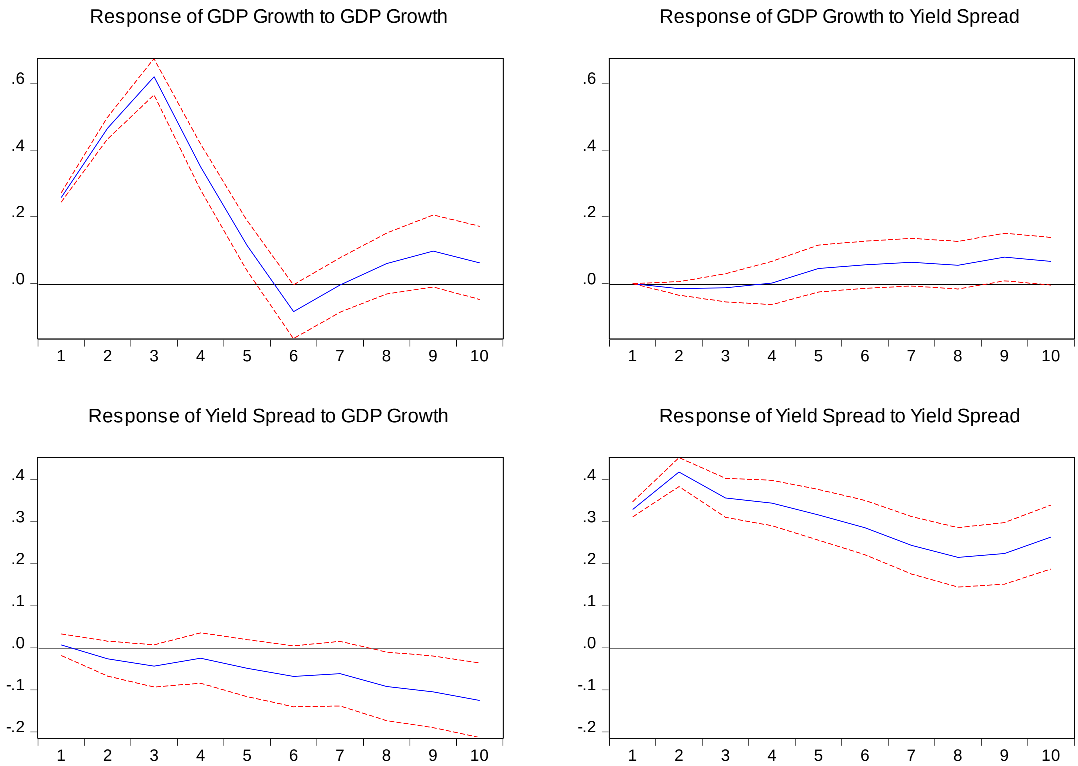


Response of Unemployment rate to Unemployment rate

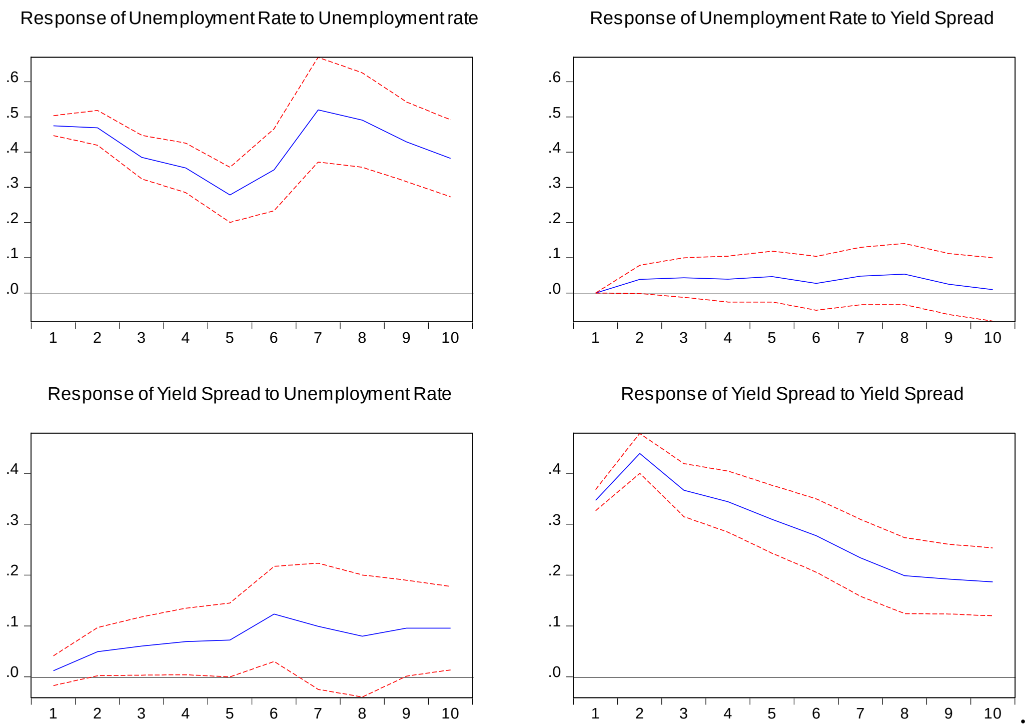


g) United States

GDP Growth VAR model



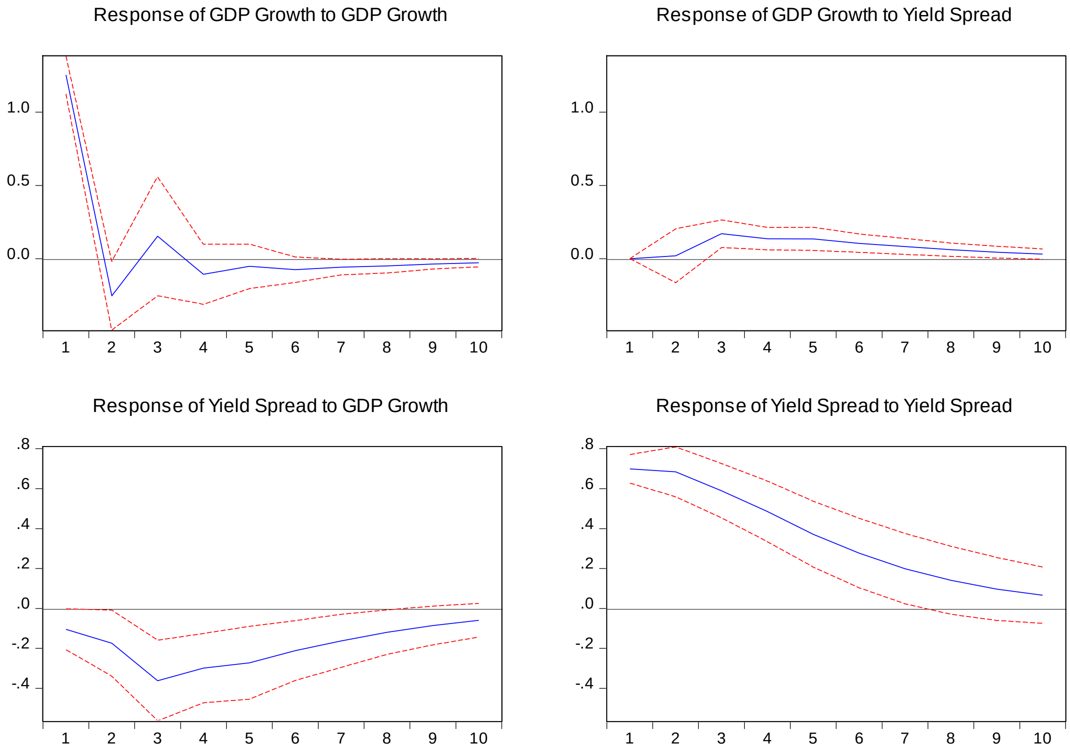
Unemployment rate VAR model



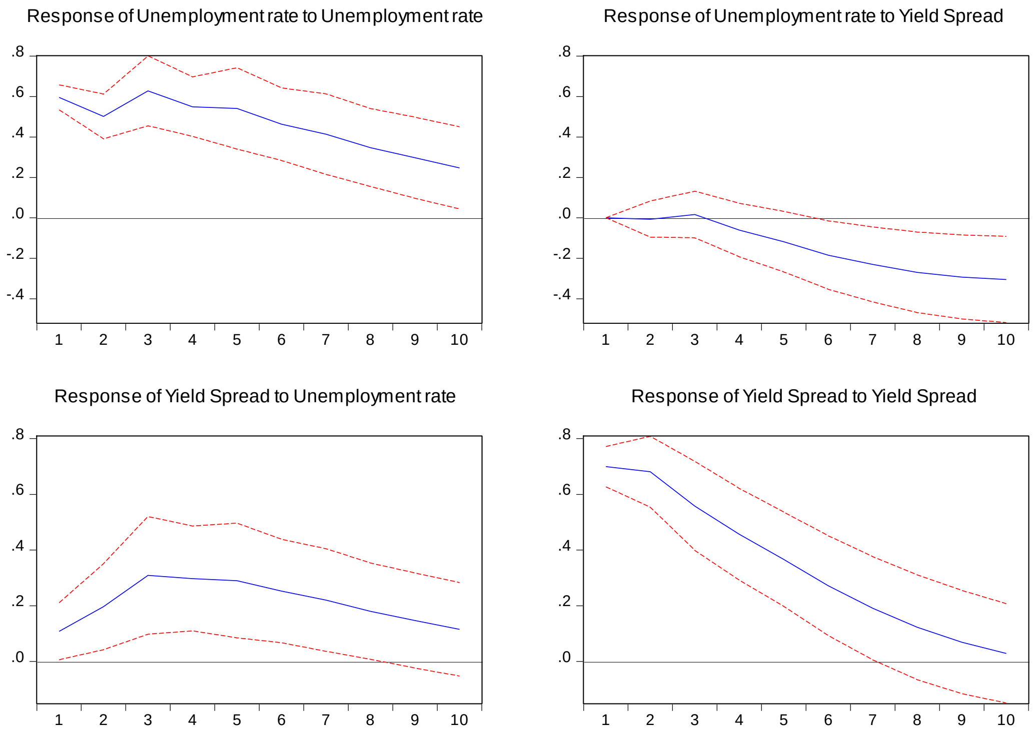
Next we have the Impulse response function on the quarterly frequency

a) Canada

<u>GDP Growth VAR model</u>

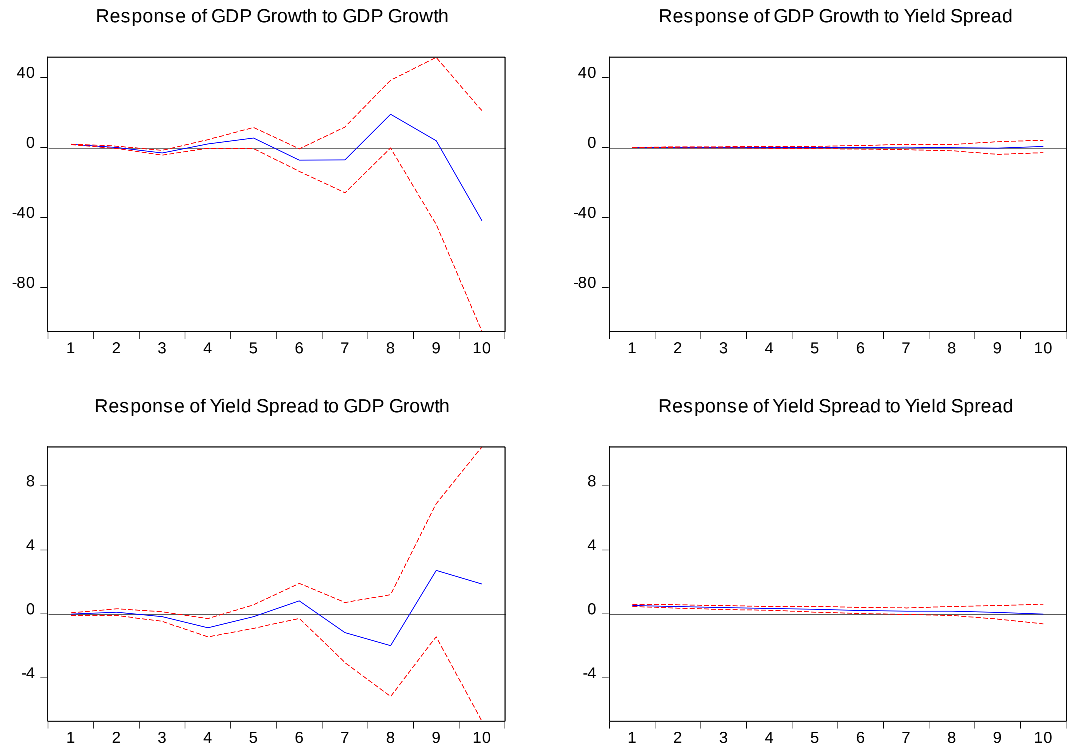


<u>Unemployment rate VAR Model</u>

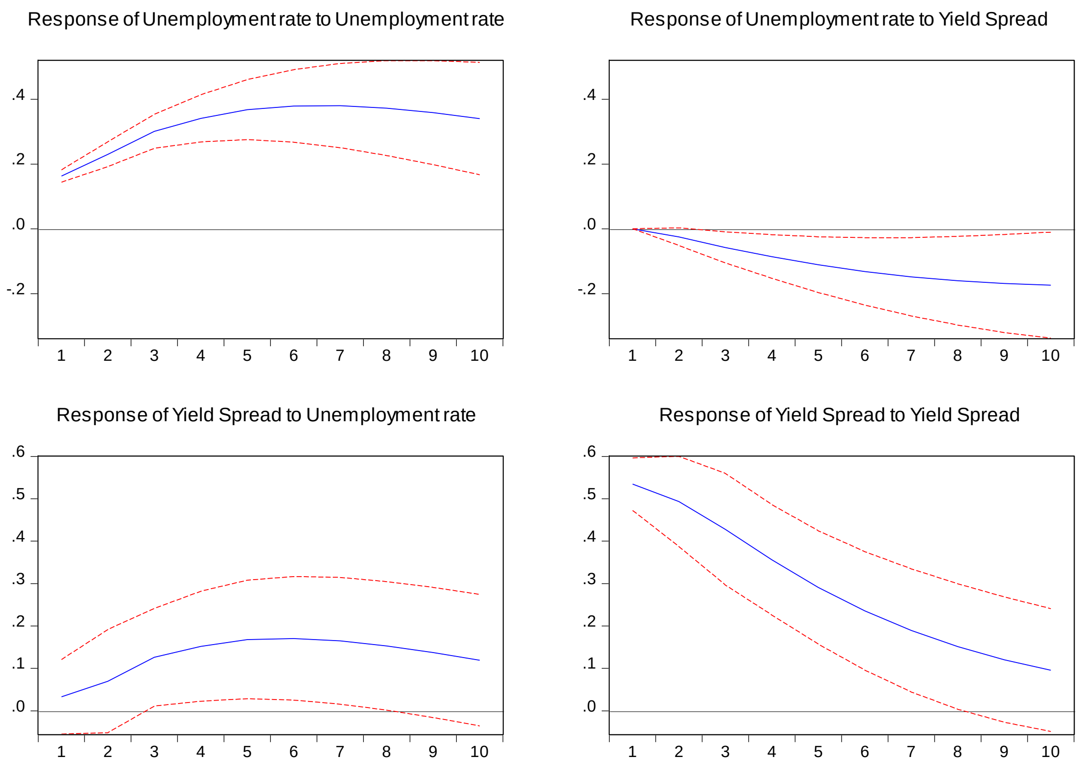


b) France

<u>GDP Growth VAR model</u>

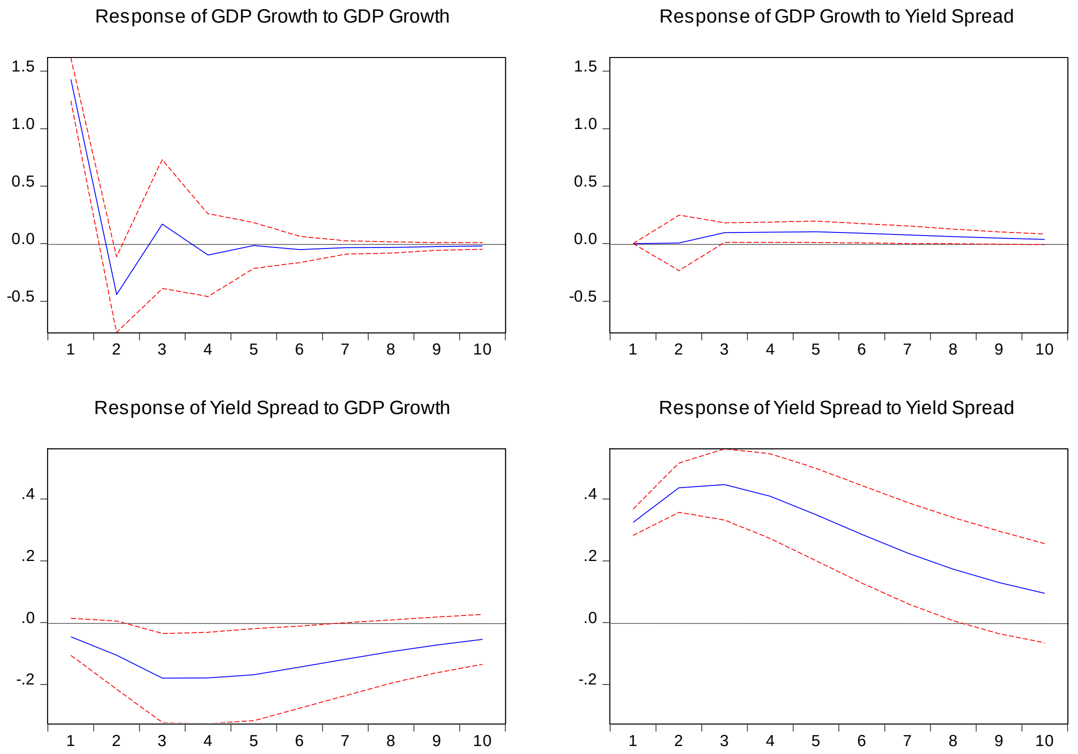


<u>Unemployment rate VAR model</u>

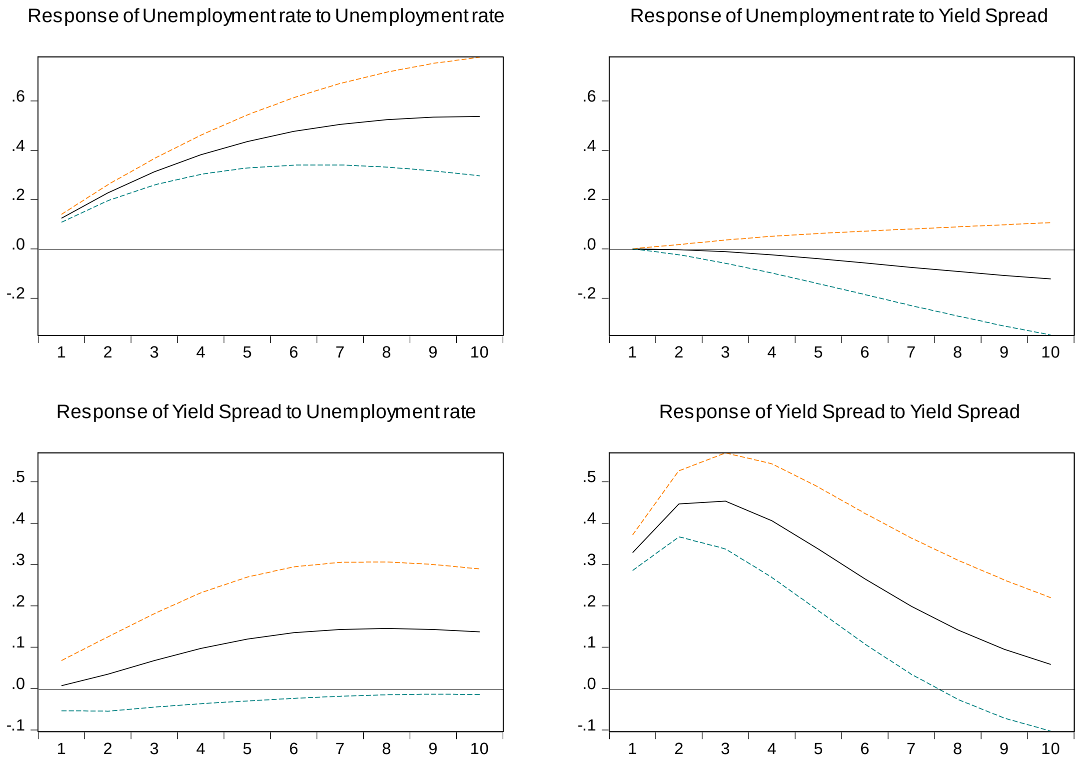


c) Germany

GDP Growth VAR model

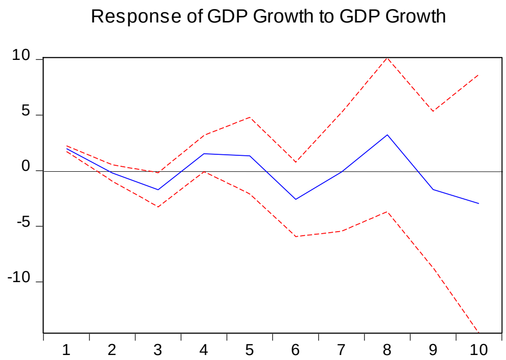


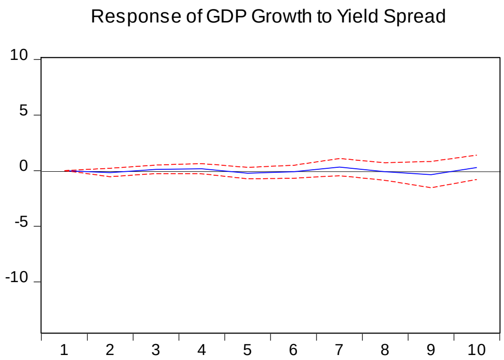
Unemployment rate VAR model

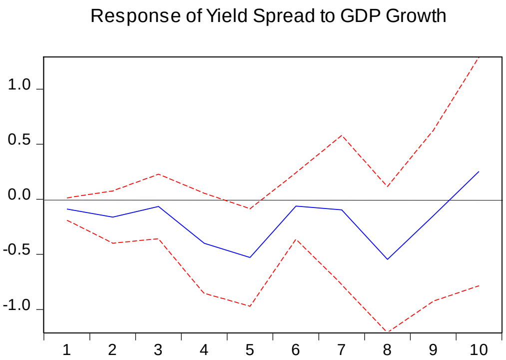


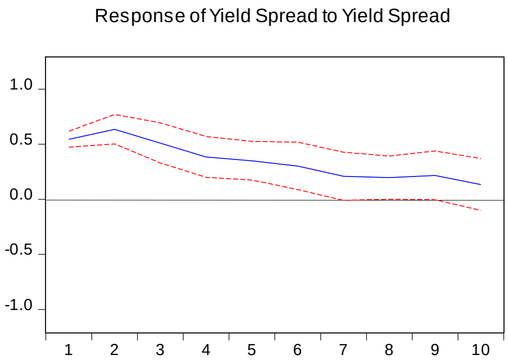
d) Italy

GDP Growth VAR model

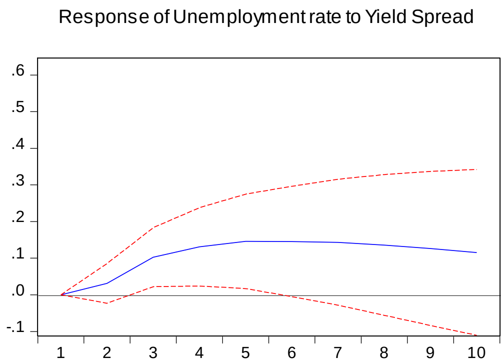


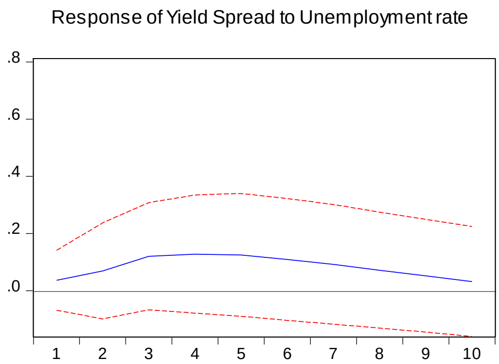


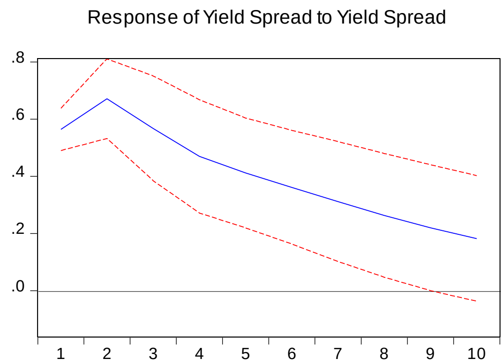




Unemployment rate VAR model



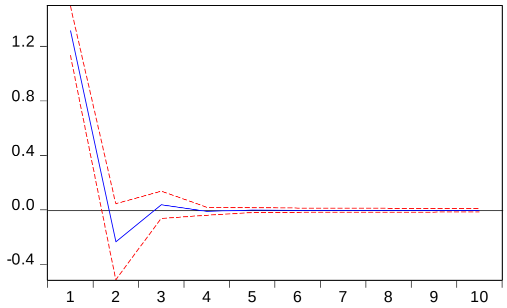




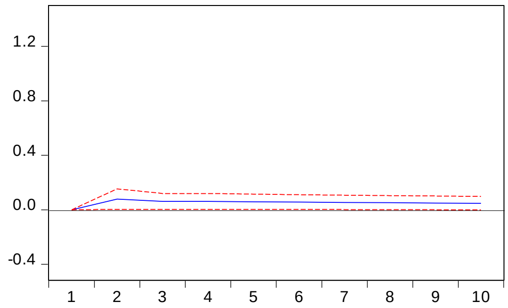
e) Japan

GDP Growth VAR model

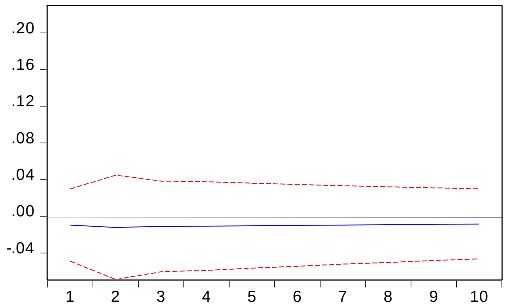
Response of GDP Growth to GDP Growth



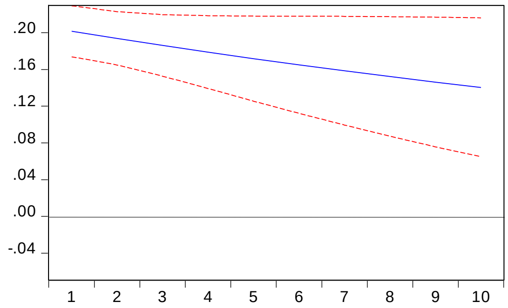
Response of GDP Growth to Yield Spread



Response of Yield Spread to GDP Growth

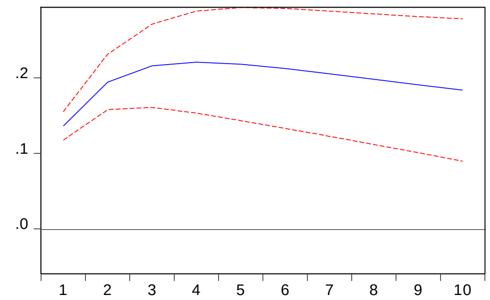


Response of Yield Spread to Yield Spread

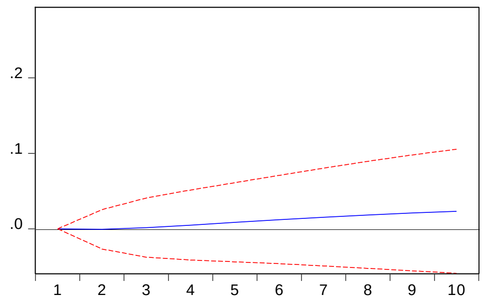


Unemployment rate VAR model

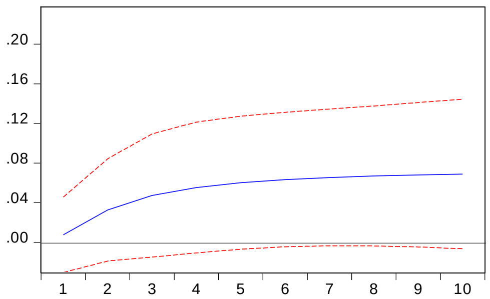
Response of Unemployment rate to Unemployment rate



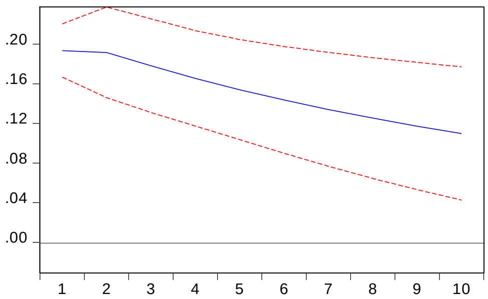
Response of Unemployment rate to Yield Spread



Response of Yield Spread to Unemployment rate



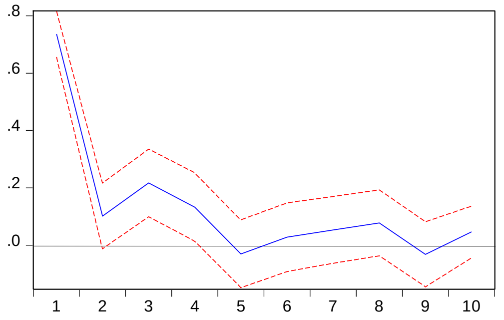
Response of Yield Spread to Yield Spread



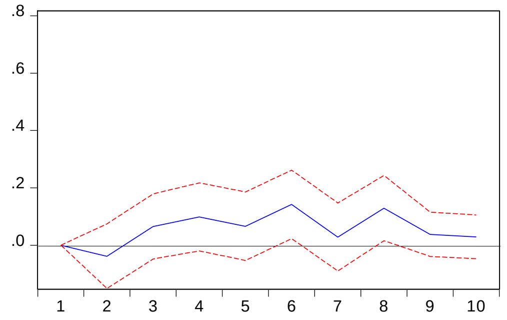
f) United Kingdom

GDP Growth VAR model

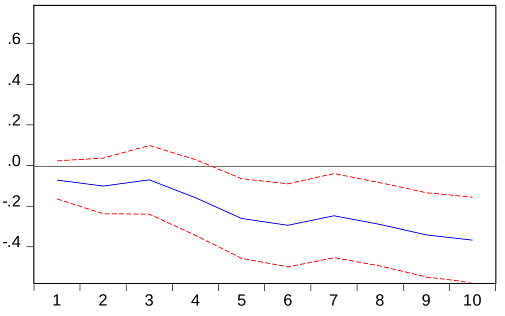
Response of GDP Growth to GDP Growth



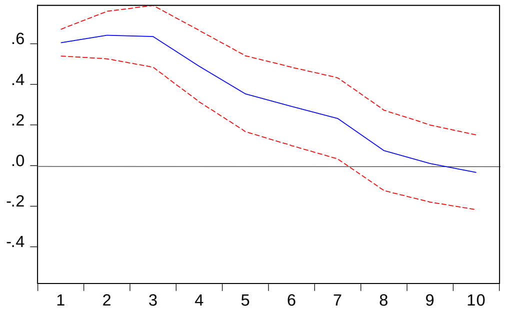
Response of GDP Growth to Yield Spread



Response of Yield Spread to GDP Growth

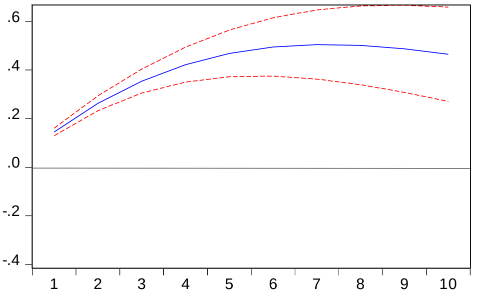


Response of Yield Spread to Yield Spread

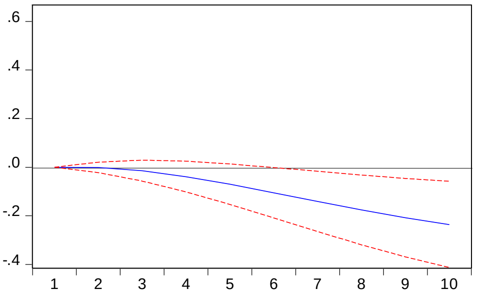


Unemployment rate VAR model

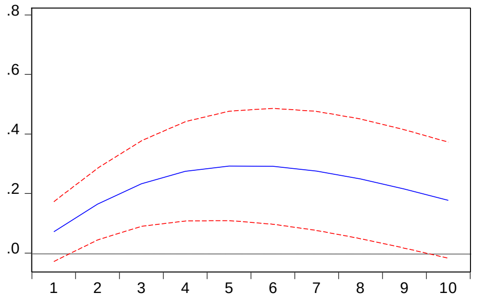
Response of Unemployment rate to Unemployment rate



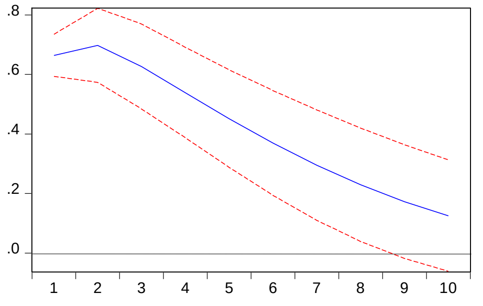
Response of Unemployment rate to Yield Spread



Response of Yield Spread to Unemployment rate

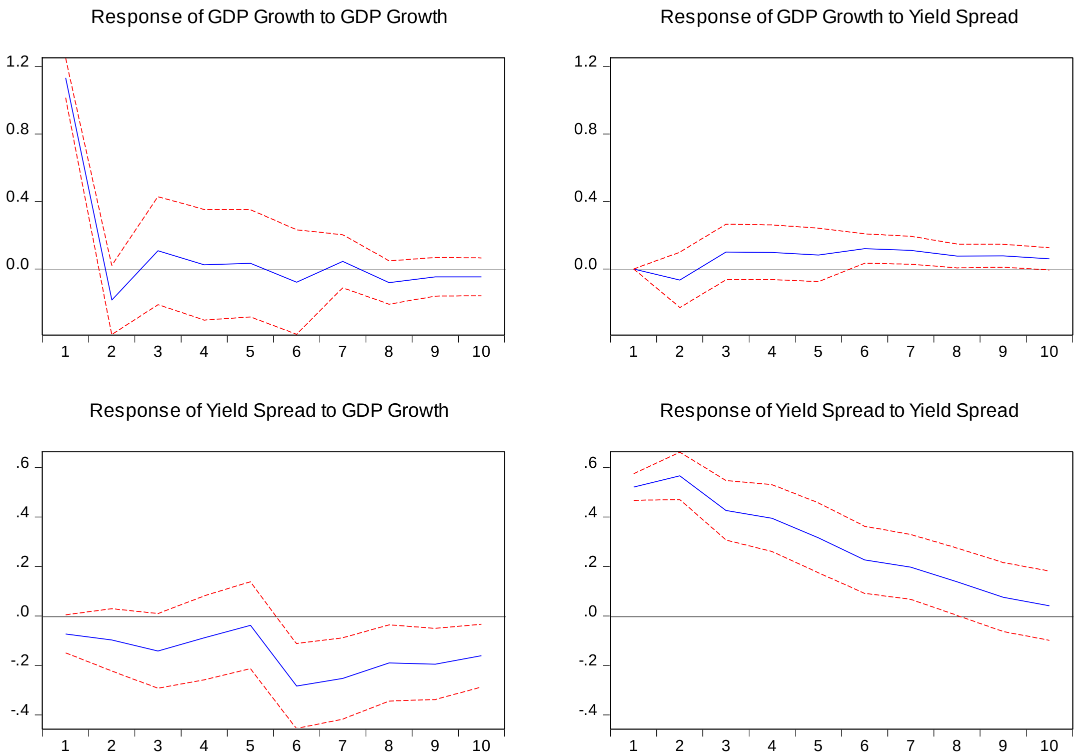


Response of Yield Spread to Yield Spread

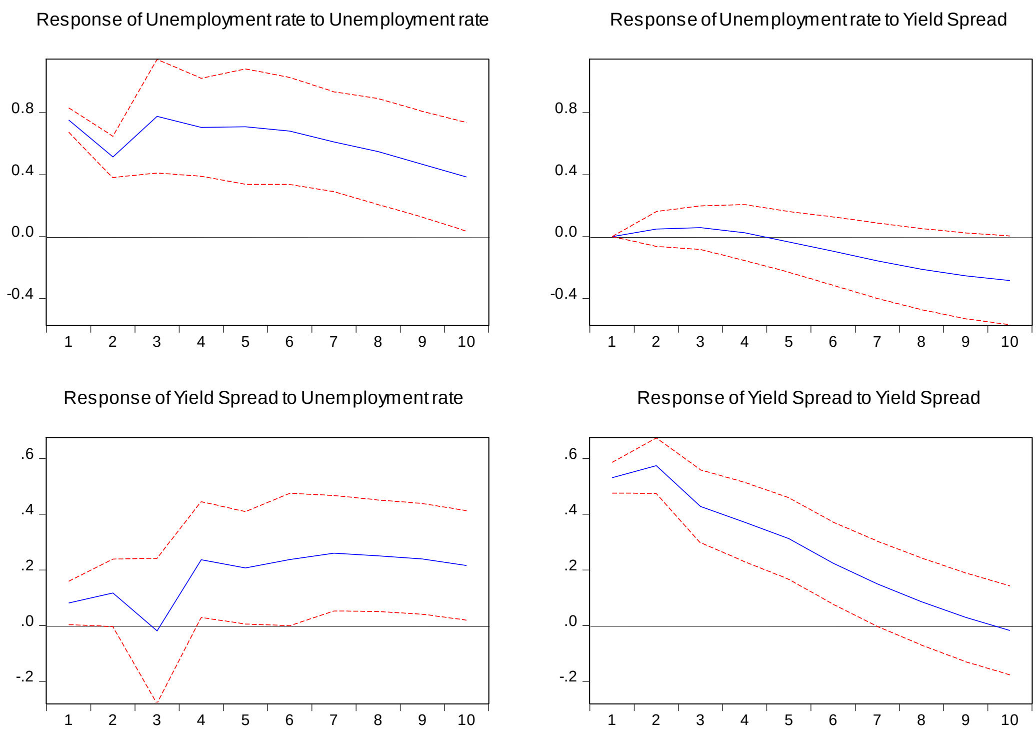


g) United States

GDP Growth VAR model



Unemployment rate VAR model



An impulse response is the reaction of any dynamic system in response to some external change. In both cases, the impulse response describes the reaction of the system as a function of time

On monthly basis GDP growth reacts intensely on the yield spread's shocks especially at the first lags where the significance is higher and it moves according to our existing literature. Cinquegrana, G., & Sarno, D. (2010) and Rubaszek, M. (2016). For Unemployment rate we can see from the graphs that the we have larger standard errors. We can also spot that the significance drops as long as we proceed to more lag. For Canada drops after the 3rd lag, for France under the 2nd and for the United States loses significance as well after the 2nd lag. For Germany, Italy, Japan and the United Kingdom our results are not significant and in the same manner as the work of Sarno, L., Thornton, D. L., & Valente, G. (2007).

On the quarterly frequency we can see as well that there is an impact of yield spread's shocks on GDP growth, even higher than the monthly frequency considering the high significance of the latter in every lag, meaning that the shocks of Yield spread bring a reaction to the respective GDP.

As for the Unemployment rate the significance is higher than of the monthly frequency but it is still not as high as GDP. The most impactful was on the U.K. where the spread is statistically more significant towards Unemployment rate.

It's important to note that their relationship considering their shocks is negative which means that an upward spike shock of the yield spread spikes the Unemployment rate upwards and vice versa. One possible interpretation for that phenomenon is the strong relationship between the Yield curve with the monetary policy. One of the goals of expansionary monetary policy is to increase aggregate demand lowering the interest rates. Lower interest rates mean that the cost of borrowing is lower. When it’s easier to borrow money, private Investors spend more money and invest more. This increases aggregate demand and GDP and decreases the unemployment rate. Blanchard, O. (2003)

7. CONCLUSIVE REMARKS

This research provided insights about the predictive power of the yield curve for the GDP growth and Unemployment rate for the G7 industrial countries. Our results, in general are consistent with the results of previous studies. The yield curve is a statistical and economical significant predictor for GDP growth proving that the size of the spread can indicate the level of economic growth as Bonser-Neal, C., & Morley, T. R. (1997) and Haubrich, J. G., & Dombrosky, A. M. (1996) point out. In most of G7 countries the leading predictor is that of the spread with the Out-of-Sample forecasting method and followed the lagged along with the spread especially in monthly frequency. In quarterly the relation is somewhat different, as for most of G7 countries spread itself was not the best predictor. It was the most suitable for Canada, Germany and 1 year for United States. Again we are in line with previous studies as for the loss of predictive power of the Yield curve after 3 years of expansion. [Estrella, A., & Hardouvelis, G. A. (1991)]

For Unemployment rate their relationship is not as significant which is not surprising following past researches Sarno, L., Thornton, D. L., & Valente, G. (2007). For our sample, its own lagged difference is mostly the top of the line predictor following its lagged difference along with spread with the exception of Canada, France and United Kingdom with the first two having better results with the leading indicator of Industrial production and United Kingdom the yield spread.

For the last part of analysis with the Vector Auto-regressive model again the estimates prove positive and statistical significance with the GDP Growth and negative with Unemployment rate. The impulse responses show the impact of the shocks of our two variables, GDP growth or Unemployment rate with the yield spread. Our results are moving at the same direction as Cinquegrana, G., & Sarno, D. (2010), meaning that the monthly data show us the standard errors larger and quarterly gives us significance.

In conclusion the yield spread forecasts are very useful tools for managerial and economic purposes and can give us insight for possible economic activity even if it has lost some of its popularity as a predicting tool through recent years changes [Hvozdenská, J. (2017)].

The contribution of this thesis is on the forecasting ability of the yield spread for the recent years as well the reaction from shocks. Another aspect that this research has examined is the possible influence of the Yield curve on Unemployment rate which is something that hasn't been expanded so much. Of course the economic activity can depend on behavioral aspects and how the majority of individual would react especially in times of shocks like the Global economic crisis of 2008 and the Covid-19 crisis of 2020.

8. APPENDIX

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8.2 Unit root test results

Unit Root tests - Monthly results		
		ADF P-Value
Canada	GDP Growth	0.0000
	Unemployment rate	0.2151
	Yield Spread	0.0000
France	GDP Growth	0.0022
	Unemployment rate	0.3463
	Yield Spread	0.0030
Germany	GDP Growth	0.0002
	Unemployment rate	0.2470
	Yield Spread	0.0786
Italy	GDP Growth	0.0016
	Unemployment rate	0.9122
	Yield Spread	0.0294
Japan	GDP Growth	0.0000
	Unemployment rate	0.5531
	Yield Spread	0.3869
United Kingdom	GDP Growth	0.0020
	Unemployment rate	0.4370
	Yield Spread	0.0214
United States	GDP Growth	0.0000
	Unemployment rate	0.0481
	Yield Spread	0.0005

Unit Root tests - Quarterly results		
		ADF
Canada	GDP Growth	0.0000
	Unemployment rate	0.3248
	Yield Spread	0.0020
France	GDP Growth	0.0005
	Unemployment rate	0.2454
	Yield Spread	0.0256
Germany	GDP Growth	0.0000
	Unemployment rate	0.2925
	Yield Spread	0.0124
Italy	GDP Growth	0.0000
	Unemployment rate	0.7050
	Yield Spread	0.0332
Japan	GDP Growth	0.0000
	Unemployment rate	0.5551
	Yield Spread	0.5655
United Kingdom	GDP Growth	0.0000
	Unemployment rate	0.1699
	Yield Spread	0.0078
United States	GDP Growth	0.0000
	Unemployment rate	0.0481
	Yield Spread	0.0011

8.3 Johansen Cointegration Tests

Johansen Cointegration Test - Monthly results			
		None P-Value	At most 1 P-Value
Canada	GDP Growth and Yield Spread	0.0000	0.0000
	Unemployment rate and Yield Spread	0.0002	0.0068
France	GDP Growth and Yield Spread	0.0001	0.0007
	Unemployment rate and Yield Spread	0.0002	0.0093
Germany	GDP Growth and Yield Spread	0.0000	0.0002
	Unemployment rate and Yield Spread	0.0325	0.0034
Italy	GDP Growth and Yield Spread	0.0000	0.0006
	Unemployment rate and Yield Spread	0.0513	0.0325
Japan	GDP Growth and Yield Spread	0.0002	0.0004
	Unemployment rate and Yield Spread	0.0046	0.0201
United Kingdom	GDP Growth and Yield Spread	0.0000	0.0001
	Unemployment rate and Yield Spread	0.0168	0.0298
United States	GDP Growth and Yield Spread	0.0001	0.0000
	Unemployment rate and Yield Spread	0.0001	0.0017

Johansen Cointegration Test - Quarterly results

		None P-Value	At most 1 P-Value
Canada	GDP Growth and Yield Spread	0,0001	0,0000
	Unemployment rate and Yield Spread	0,0001	0,0045
France	GDP Growth and Yield Spread	0,0000	0,0002
	Unemployment rate and Yield Spread	0,0431	0,0120
Germany	GDP Growth and Yield Spread	0,0000	0,0017
	Unemployment rate and Yield Spread	0,1012	0,0117
Italy	GDP Growth and Yield Spread	0,0000	0,0006
	Unemployment rate and Yield Spread	0,0712	0,0467
Japan	GDP Growth and Yield Spread	0,0000	0,0006
	Unemployment rate and Yield Spread	0,0410	0,0125
United Kingdom	GDP Growth and Yield Spread	0,0000	0,0001
	Unemployment rate and Yield Spread	0,0401	0,0282
United States	GDP Growth and Yield Spread	0,0001	0,0000
	Unemployment rate and Yield Spread	0,0008	0,0138

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