

THE YIELD SPREAD AND INFLATION AS ECONOMIC FORECASTING VARIABLES IN THE UK

JACOB HALÉN DAHLSTRÖM



LUND UNIVERSITY
School of Economics and Management

Department of Economics

BACHELOR'S THESIS

SUPERVISED BY BIRGER NILSSON, DOC.

SPRING, 2015

ABSTRACT

- Title:** The Yield Spread and Inflation as Economic Forecasting variables in the UK.
- Keywords:** Term Structure, Yield Spread, Inflation, Multiple Regression Model, Forecasting, GDP, United Kingdom
- Course:** NEKH01, Bachelor's Thesis in Financial Economics, 15 ECTS.
- Author:** Jacob Halén Dahlström
- Contact:** nek10jh2@student.lu.se
- Supervisor:** Birger Nilsson, Doc.
- Aim:** To investigate the economic predictive powers of the yield spread and inflation in the United Kingdom.
- Methodology:** Quantitative study of financial and macroeconomic data, using econometric OLS regressions.
- Theory:** Theoretical framework of the relationship of the term structure and economic growth.
- Conclusion:** The yield spread as a single explanatory variable has some economic predictive capacity in the United Kingdom during the sample period, as where the variable of inflation has less significance in our models.

TABLE OF CONTENTS

1. INTRODUCTION.....	4
1.1 Background.....	4
1.1.1 Earlier Research	5
1.2 Problem discussion.....	6
1.3 Purpose.....	7
1.4 Delimitations.....	7
2. THEORY.....	8
2.1 The Yield Curve.....	8
2.1.1 Types of Yield Curve	8
2.2 Relationship Yield-Maturity.....	10
2.3 Relationship inflation and GDP.....	10
2.4 Relationship inflation and yield spread.....	11
2.5 Choice of country.....	11
2.6 Choice of spread.....	11
2.7 Econometric model.....	12
2.7.1 Assumptions.....	12
2.8 Econometric problems.....	13
2.8.1 Multicollinearity.....	13
2.8.2 Heteroscedasticity.....	14
2.8.3 Autocorrelation.....	14
3. METHODOLOGY.....	15
3.1 Data Sample.....	15
3.2 Data definitions.....	15
3.3 Regression model.....	16
3.4 Forecast model.....	17
4. EMPIRIC RESULTS.....	18
4.1 Chart view of data.....	18
4.1.1 Hypothesis testing (F-test)	22
4.2 Forecast model.....	24
4.2.1 Out-of-sample forecasting results	24
4.2.2 Root Mean Squared Error model	26
4.2.3 Theil Coefficient.....	27
5. ANALYSIS.....	29
6. CONCLUSION & FUTURE RESEARCH.....	30
7. REFERENCES.....	32
8. APPENDIX.....	34
8.1 Regression Raw Data.....	34
8.2 In-sample Regressions.....	35
8.3 Forecast Results.....	39
8.4 Forecast Regressions.....	43

1. INTRODUCTION

1.1 Background

The ability to predict tomorrow's economic activity has been a debated topic for centuries. The studies of the business cycle and how its variables can be used to predict future economic activity have been many. The use of differences in interest rates on different financial assets have received a lot of interest from market analysts and policy makers, to academic economists over the past 25 years. One of the first to make such a discovery was Stock and Watson (1989), who found that using two interest rate spreads - in their case the 10-year Treasury bond and the 12-month Treasury bill - they could construct an index of much higher explanatory power of leading economic indicators. 1991 Estrella and Hardouvelis presented a study of the yield spread between the 10-year US Treasury bond rate and the 3-month US Treasury bill rate and how it over time contained predictive information about the GDP and the probability of a recession (Hamilton and Kim Dong, 2000). The reason the yield spread between long-term and short-term bonds is an important variable when predicting future economic activity is because a positive spread (positive sloped yield curve), when the long-term interest rates are higher than the short-term interest rates, is associated with an increase in the GDP. This is because the belief of the future is positive, rates are higher tomorrow than today. The same goes for when there is a negative yield spread, less interest tomorrow than today (Bonser-Neal and Morley, 1997). This subject will be revisited later in the paper. In the case of recessions, which is not a subject we will discuss further in this paper, the general idea is that when the outlook of today seems worse than the outlook of tomorrow one will move one's money to a more long-term investment (in this case Treasury bonds). This notion reflects the larger markets, and is why the concept of using the spread of term structures with different maturities as an explanatory variable is used in this paper to try to predict future economic movement. Although the yield spread has been proven to have a significant predictive power in the United States, there have been fewer studies on the major European countries. Earlier studies attest to the fact that only countries with well-developed financial markets that have been around for some time, show positive statistical significance between the economic growth and the yield spread (Moffatt and Zang, 2012). United Kingdom is one of these countries that live up to the demands of a true reflecting and well-developed financial market.

Since this paper only focuses on the possible predictive powers of certain economic variables I have chosen to limit the investigation to the variable of the yield-spread, and to also add a macroeconomic variable I will incorporate the consumer price index as a measure of inflation. The expectation of higher inflation have shown to influence monetary policy makers, which in turn will influence the monetary output and the official bank rates and so the economic growth (Smets and Tsatsaronis, 1997).

1.1.1 Earlier Research

There is not one unified theory that can explain the relationship between the yield curve and economic activity, although there are many studies showing empirical evidence that supports the relationship theory. As previously stated, monetary policy can determine interest rates and so also influence the yield curve and the steepness of it. When tightening the monetary policy, a rise in the short-term interest rates are usually to be expected - this operation is foremost to reduce inflation (Estrella and Trubin, 2006). One of the major previous studies of the relationship between different macroeconomic variables and the prediction power of tomorrow's economic activity is a study done by Stock and Watson (1989). They used 55 macroeconomic variables, which in later adaptations have been narrowed down to seven. Of these seven variables the spread between the 10-year and the 1-year US Treasury bond had one of the best capacities to predict future economic activity (Dotsey, 1998). This is also why this paper only focuses on the financial variable of the yield spread. The yield spread is the difference between the interest rates (yield) of two securities with different maturities at a point in time (Bonser.Neal and Morley, 1997). The spread contains a number of economic variables with information regarding economic activity, such as difference in nominal interest rates on bonds with different maturities, the expected difference in inflation and a term premium (Dotsey, 1998). The prediction powers of using only the yield spread were tested by Estrella and Hardouvelis (1991) when they performed a study of 32 years of yield spread-data from 10-year Treasury bonds and 3-months Treasury bills. The results showed that the spread contained predictions of cumulative economic growth for up to four years in the future (Estrella and Hardeouvelis, 1991). More recent studies on the yield spread and its prediction powers have been focused on the ability to signal a potential recession. Estrella and Mishkin (1998) were early on adapting this theory and showed it was one of the best out-of-sample predictors of the probability of recession happening within the next year (Dotsey, 1998).

1.2 Problem discussion

There are many studies presenting evidence supporting the use of the yield spread as a future economic indicator, although these studies have been done on the financial- and macroeconomic markets in the United States. Considering the amount of studies done quite few focus their attention to other markets than the US. To make such econometric models, one require long time series of yield data of the bonds and the bond market must be liquid, meaning the bonds must be issued regularly (monthly or quarterly) and they must be frequently traded (reflecting market expectations). This means only certain countries with well-developed financial markets, with sample data stretching far enough back in time, fit the needs to make an accurate regression analysis (Bonser-Neal and Morley, 1997). The United Kingdom has had a well functioning financial market for decades, and as a large market they have a liquid bond market, which makes the UK a good sample country for this paper. Previous studies, e.g. Dotsey (1998) and Stock & Watson (2003), shows that the predictive power of the yield spread alone has declined after 1985 but still holds a greater predictive power than most other leading indicators used (Zhang and Moffatt, 2012). To investigate the ability to predict future economic activity this paper will also include the variable of inflation. The *Consumer Price Index* reflects the level of inflation in a country and by including this variable, which is a powerful monetary tool in stimulating the economy and have previously proven to correlate with the level of economic growth, in the regression we might be able to get a stronger forecast model and level of explanatory power.

This thesis will therefore investigate how well the yield spread of the 5-year Treasury bond and the 6-month Treasury bill can explain the level of real GDP growth in the United Kingdom. Additionally, the variable of inflation will be included in the regression model to add to the explanatory power. Once established to what extent the GDP can be explain by these parameters, an in-sample forecast of between 1-16 quarters ahead will be made to see the real level of predictive powers.

Consequently the main thesis question formulates as following:

Does the yield spread and inflation act as significant variables in predicting economic activity in the future in the United Kingdom?

1.3 Purpose

The purpose of this thesis is to determine to what extent the financial market data of Treasury securities and their differences in yield, combined with the growth level of inflation, can explain the real growth levels of the Gross Domestic Product (GDP) in the United Kingdom.

1.4 Delimitations

The delimitations of the this thesis are:

- The time period chosen is between Q1 1989 and Q3 2014. This specific period is chosen mainly to include as many observations as possible, since the more observations included, the more explanatory power there is in the regression. Since the UK financial market is well-developed and well-documented, the time period could stretch much further back in time, but in this paper the delimitation have been set to a time period of 26 years and three quarters.
- The multiple regression models variables consist of quarterly collected data. This due to that the GDP official data is only published once every quarter, which makes this a necessity. Some of the previous studies shows the use of a large number of explanatory variables, there among non-financial variables, although this paper have chosen to include only two - the yield spread and the inflation growth in the United Kingdom, mostly because Stock and Watsons previous study (1989) concluded that the Treasury yield spread had the best capacity to predict economic movement out of 55 variables.

2. THEORY

2.1 The Yield Curve

2.1.1 Types of Yield Curve

The yield curve shows the relationship between the interest rate (yield) of fixed income securities with equal credit quality, at a certain point of time, but with different maturity dates (Investopedia). There are mainly three types of yield curve shapes: *positive yield curve*, which tells that longer maturities have higher interest rates than e.g. a bond with shorter maturity due to the risk factor increases over time. *Negative yield curve*, have an inverted relationship between the interest rate and the maturity, whereas the risk compensation for longer maturities is less than for shorter maturities, so this can be a sign of an upcoming recession. *Flat yield curve* is when the difference between long- and short-term interest rates is close to zero, which can interpret that the prediction of future economic climate is not greater or worse than today.

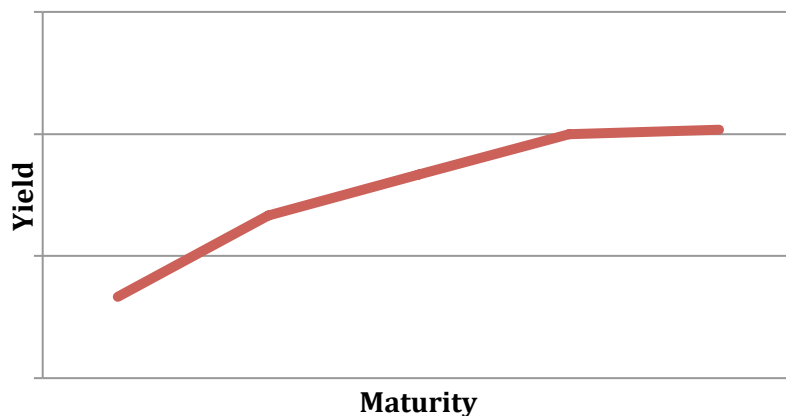


Figure 1. Positive Yield Curve

The figure shows the relationship between the bond yields and the maturity lengths. The shape of the positive yield curve results from higher interest rates (or yields) from bonds with longer maturity, due to the outlook of better economic climate in the future and the increased exposure of risk over time, and lower levels of interest rates from bonds with shorter maturity.

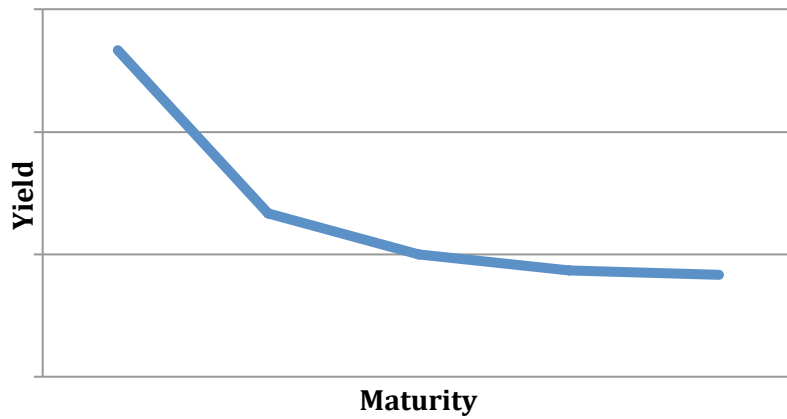


Figure 2. Negative Yield Curve

The negative yield curve with its downwards-sloping curve results in lower interest rates from bonds with longer maturities, and higher interest rates from bonds today. This can be interpreted as prediction that interest rates are going to fall in the future, and a recession might be coming our way. The negative yield curve is usually followed by a flat yield curve, and then a positive yield curve.

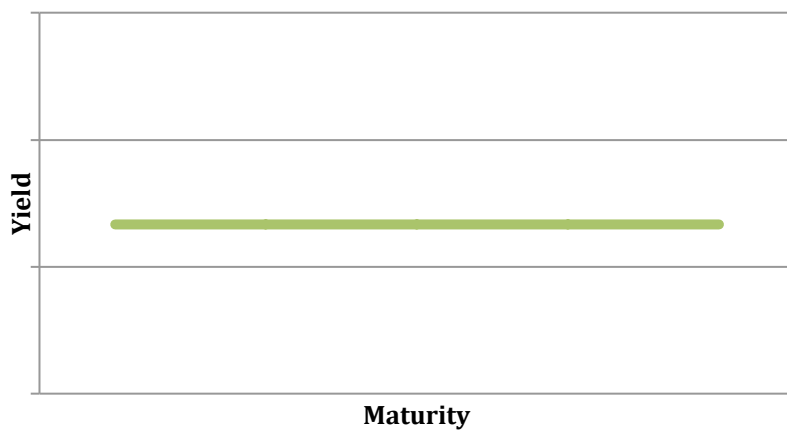


Figure 3. Flat Yield Curve

The flat yield curve results from when the interest rates of bonds with long maturities are equal to bonds with short maturities. This might be a sign of expectations of future inflation are falling, or the due to the anticipation of a slowing economic growth.

2.2 Relationship Yield-Maturity

To get a greater sense of how the yields in relations to their maturities are accounted for, one must have a basic knowledge of macroeconomics and how the repurchase-rate of a country's Central Bank and the monetary policy influence the yield of government bonds.

Macroeconomic theory says that tightening the supply of money will result in the short-term interest rates to be raised, due to the same demand for fewer funds. The long-term expectations of interest rates will also change due to the change in expected inflation, although not in the same extent (Estrella and Mishkin, 1997). The tightening of monetary funds slows down the economy and inverts, or flattens the yield curve. When on the other hand the monetary base expands, the short-term rate will decline in greater extent than the long-term rate which leads to a less flattened yield curve (Estrella and Trubin, 2006). Although the monetary policy of a country is a significant factor in explaining the yield curve, it is not the only determinant. The *market segment theory* argues that the shape of the term structure is first of all determined by the supply and demand of the instrument, whereas two investors buy the securities with different maturities influencing the demand and supply of these and so the interest rates. Another theory is the *pure expectation theory* that makes the assumption that investors are indifferent to different maturities as long as they obtain the highest total return during the investment period. The *liquidity premium theory* argues that investors prefer short-term securities because they have less of an interest rate risk. This increases the demand of short-term securities, which makes the market more liquid for these instruments, and the yields lower than for long-term securities. This makes the yield curve upward sloping, due to the lower yields for short-term maturities than for long-term (Stander S, 2005).

2.3 Relationship inflation and GDP

The relationship between level of inflation in a country and the growth in real GDP is an important macroeconomic foundation that gives the Central Bank, which controls the monetary policy, the tools to intervene in the economic development in a country. By increasing the repurchase (repo) rate, it forces banks to increase the interest rate for lending which slows down the economic growth and the stagnation in inflation. In a different scenario, increasing the monetary base would lower the interest and increase inflation, which in turn would have a positive effect on the economic growth (Kahn and Senhadji, 2000).

2.4 Relationship inflation and yield spread

The expected inflation has a major impact on monetary policy makers and the way to predict the price levels of tomorrow. If the expected inflation is believed to increase, the policy for monetary output might be decided to decrease in order to slow down the increasing price-rate in comparison to disposable wages. While doing so the official bank rate, most likely, goes up - the short-term interest rate falls and thereby creates a more positive (or less negative) yield spread. In conclusion, although the variables do not have a direct relationship, one might influence the other.

2.5 Choice of country

In order to be able to perform a study based on both macroeconomic data and financial data, the country in question must have reliable data concerning its inflation and real economic activity. It is crucial that the financial market is well established and that the government is stable and not an object of defaulting risk. The market data must be transparent and the country must have a significant amount of historical financial data, whereas a larger amount of data empowers the forecasting model (Bonser-Neal and Morely, 1997).

2.6 Choice of spread

When choosing the debt securities to test the spreads prediction powers, it is crucial that the securities are frequently traded and reflects the markets true expectations to high extent (Bonser-Neal and Morley, 1997). The choice of a security with a short maturity and a long maturity has proven efficient in previous studies, such as Estrella and Hardouvelis (1991) were they used a 10-year Treasury bond and a 3-month Treasury bill to define their spread. This examines the relationship between the long- and short interest-rates, and defines the momentarily expectations of short-term and long-term economic development. The efficiency of these spreads and the criteria of the market limits the countries where such studies can be performed, which beg the questions to what extent the model is applicable. In United Kingdom, the 5-year Treasury bond and the 6-month Treasury bill are somewhat more liquid securities and therefor reflects the true interest movements, that is why these are the chosen spreads for this paper.

2.7 Econometric model

The *multiple regression model* examines the case where a dependent variable Y is assumed to be defined by two (or more) explanatory variables, X_2 and X_3 , this in difference to the *single linear regression*, which examines the relationship between a single explanatory variable X and the dependent variable Y (Dougherty, 2011). The solution to estimate the equation used in this model is called the *Ordinary Least Square* criterion, or *OLS*. The criterion states that estimates of β_1 and β_2 , called b_1 and b_2 , should be chosen so that the difference for every value between the estimated and the actual is squared and made smallest possible (Dougherty, 2011).

2.7.1 Assumptions

When using time series data the data generation process (DGP) differs from when using cross-sectional data or panel data, since the time dimension imposes a natural order. This means the observations will be indexed using t instead of i . Also since the data for times series is continuous, not discrete, and it is not usually possible to work in continuous time, the series are converted into discrete form by dividing the data into regular intervals. The frequency of the intervals is to be determined by the nature of the data.

- i.* The model is linear in its parameters and correctly specified, meaning that the dependent variables include a β as a simple factor and that there is no relationship built-in between the different β s. The model is shown below.

$$Y_i = \beta_0 + \beta_2 x_{2i} + \beta_3 x_{3i} + \dots + \beta_K x_{Ki} + u_t$$

- ii.* The disturbance term u_t has the expected value of zero, this since it sometimes will be positive and sometimes negative, but not have a systematic tendency in one of the directions.

$$E(u_i) = 0 \text{ for all } i$$

- iii.* The variance of the disturbance term u_t is constant, meaning that the value of each observation is drawn from a distribution with a constant population variance - this is called *homoscedasticity*.

$$\text{Var}(u_i) = \sigma^2$$

If $\text{Var}(u_i) \neq \sigma^2$ for some of the i , then there is a case of *heteroscedasticity*.

- iv. The values of the disturbance terms have their own distributions, meaning that it should not be any systematic association between the values of any two observations - no *autocorrelation*.

$$\text{Cov}(u_i, u_j) = 0 \text{ if } i \neq j$$

- v. The disturbance term has a normal distribution and an expected value of zero, and a variance of σ^2 . If u is normally distributed, this means the regression coefficients will also have a normal distribution (Dougherty, 2011).

$$u_i \sim N(0, \sigma^2)$$

2.8 Econometric problems

Some common problems may occur when dealing with regression models, especially when it comes to time series data. These issues may compromise the validity of the results.

2.8.1 Multicollinearity

Multicollinearity defines when two or more explanatory variables in a multiple regression model have high correlation, which leads to higher population variance of their coefficients and higher risk of obtaining irregular estimates of the coefficients. If this occurs the model is said to suffer from multicollinearity (Dougherty, 2011). The presence of multicollinearity does not make the model wrong or unreliable, but since the standard errors will be larger than without multicollinearity, one might reject the results of the model since the standard errors is a sign of unreliable estimates.

2.8.2 Heteroscedasticity

Heteroscedasticity defines the case where the variances of the model errors are no longer constant; instead they are a function of the explanatory variable of x_i , which makes the magnitude of the errors to increase with the number of x_i . This defies the first Gauss-Markov assumption that the least squared estimators are no longer BLUE, where the B stands for best, as in there are other estimators that have smaller variances and are still unbiased (Dougherty, 2011). One can compensate for heteroscedasticity by recognize that the magnitude of the model errors increase with the x_i .

2.8.3 Autocorrelation

Autocorrelation refers to the condition of the disturbance term, where the term can be determined independently of its values in the other observations. The disturbance term picks up influence of variables affecting the dependent variable that is not included in the regression equation. Meaning that there is a trend in the error terms generated by excluded variables, thus it is not the best estimation whereas there are other estimates that have smaller variance and are unbiased (Dougherty, 2011).

3. METHODOLOGY

3.1 Data Sample

The econometric model has two explanatory variables, x_2 and x_3 , these are represented by the yield spread of Treasury securities and the percentage growth in inflation. The dependent variable Y consists of the cumulative growth of real GDP, collected through Data Stream. Since the GDP is given quarterly, all data included in the models are also presented quarterly

The yield spread consists of the difference in the yield between the 5-years Treasury bond and the 6-month Treasury bills. The yield data is collected and compiled by the Bank of England, and the choice of the yield spread have as previously stated shown to be efficient (Bank of England). These securities regularly have a monthly issuance, and since we use quarterly data in this paper, the yields are quarterly averages of each of the securities. The Consumer Price Index (CPI) reflects the level of inflation and is quarterly assessed and computed to make it seasonally adjusted as following: $\pi_t = (CPI_t - CPI_{t-4})/CPI_{t-4}$. This data is also collected through Data Stream.

3.2 Data definitions

The dependent variable consists of cumulative real GDP growth, which is seasonally adjusted. This is between quarter k and $k+t$, and the used definition originates from previous research by Estrella and Hardeouvelis (Estrella and Hardeouvelis, 1991).

$$Y_{t,t+k} = (400/k)[\log(y_{t+k}/y_t)] \quad (1)$$

The first explanatory variable, the yield spread, has a yield curve made out of the 5-year UK Treasury bond yield denominated R^L , and the 6-month UK Treasury bill denominated R^S . The yield (or interest rate) spread, denominated $SPREAD$, is the difference between the long-term interest rate and short-term interest rate These Treasury securities are quarterly averaged calculated (Estrella and Hardouvelis, 1991).

$$SPREAD_t = R_t^L - R_t^S \quad (2)$$

In theory, the more information about different spreads of different maturities one would put in the regression, the more accurate result it would produce. Although this paper just try to establish a significant correlation between the yield spread and the cumulative change in real GDP. Hence, this model only uses one yield spread (Litterman and Scheinkman, 1991).

The second explanatory variable, the Consumer Price Index (CPI), is seasonally adjusted out of its quarterly data by the following way.

$$\pi_t = (CPI_t - CPI_{t-4})/CPI_{t-4} \quad (3)$$

3.3 Regression model

The multiple regression model used will look the following:

$$Y_{t,t+k} = \beta_0 + \beta_1 SPREAD_t + \beta_2 CPI_t + u_t$$

Whereas the $Y_{t,t+k}$ is the cumulative GDP growth explained in equation (1), the $SPREAD_t$ is the difference between the long- and short-term Treasury interest rate, the CPI_t is the Consumer Price Index as a measure of inflation, and u_t is the disturbance term, or error term. To be able to establish a forecast model, predicting future economic activity, we must first establish the correlation between the yield spread and GDP, and CPI and GDP - and also how they jointly correlate with the GDP. To evaluate the relationships we will first look at the regression of model 1, containing only the yield-spread variable as the independent variable and the GDP growth as the dependent variable. Secondly we will look at the regression of model 2, containing both the yield-spread and the CPI as the independent variables and the GDP growth as the dependent. To further evaluate these results we will hypothesis test the variables, where we hypothesis that μ is equal to a specific value μ_0 as a null hypothesis, and then make an alternative hypothesis which rejects the null hypothesis (Dougherty, 2011).

In our case we try to examine if the yield spread and inflation have a statistically and significantly relationship with the cumulative GDP in the United Kingdom. Before performing a hypothesis testing we will present the relationships of yield spread and real GDP growth, and inflation and real GDP growth visually, this so that we can examine their potential relationships in a time series and get a casual understanding of their interaction.

3.4 Forecast model

If a relationship is established between the variables we will perform an out-of-sample forecast for the last 5 years of the sample (2009:3 to 2014:3) based on the previous 20 years and a quarter (1989:1 to 2009:2). This will give us a forecasted estimation of the cumulative GDP growth for the final 5 years, which then is compared to the actual values of the cumulative GDP growth for the final 5 years. This method will give us an understanding of just how significant the two explanatory variables are in predicting future economic movement. To measure the accuracy and reliability of the results two more test will be used: the Root Mean Squared Error model (*RMSE*) and the Theil Coefficient.

4. EMPIRIC RESULTS

4.1 Chart view of data

Below we have a chart view of the statistical data of both the yield spread (5-year T-bond and 6-month T-bill) and the inflation in comparison to the real GDP growth of the UK between the period of 1989:1 and 2014:3.

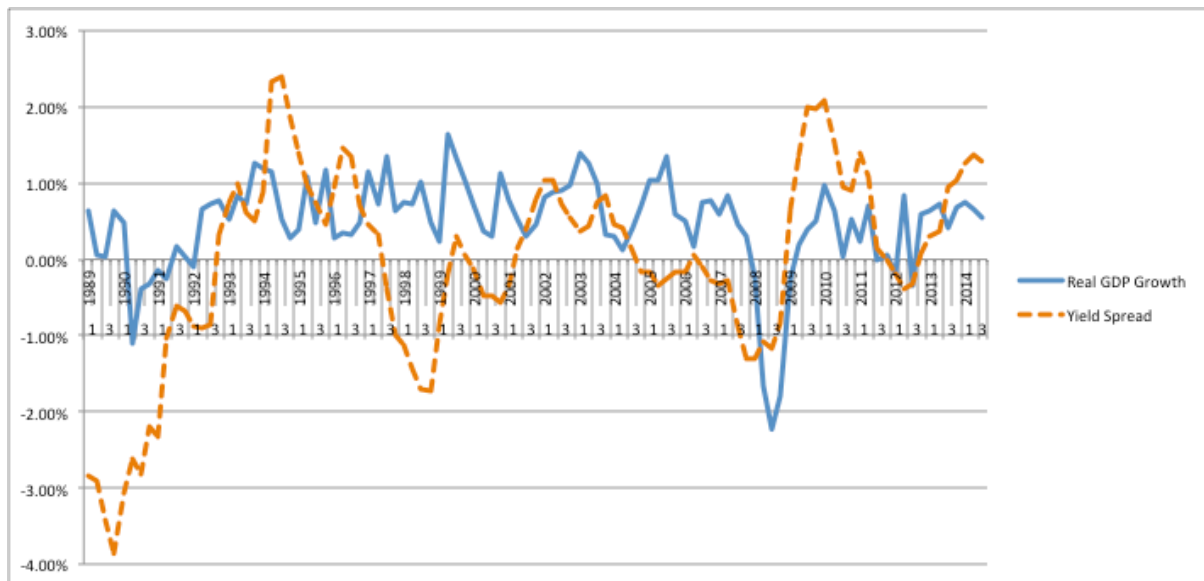


Figure 1. Yield Spread and Real GDP Growth

The chart above shows the explanatory variable of the yield spread, based on the 5-year Treasury bond and the 6-month Treasury bill, and the dependent variable of the real GDP growth rate change (in percentage) from the period of 1989:1 to 2014:3

The chart does not give a clear view of the two variables interaction, mostly because of the very different levels of volatility and interest rates, where the yield spread in general have a much higher level of volatility. Despite this one can see a indicating drop and rise in the level of real GDP growth which has been shown by the yield spread a couple of months beforehand. This is visually exemplified in 1989 Q4 where the yield-spread curve rose almost 1.8 percentage points, which later was shown in real GDP growth in 1990 Q1 when it rose by 1.2 percentage points. In 2002 Q1 the yield-spread drop by 0.7 percentage points and the GDP growth soon thereafter decreased by 1.3 percentage points in 2003 Q1.

In 2008 Q3 after the big *Credit Crunch*, the yield-spread rates rose by almost 3.2 percentage points in an effort to stimulate the British economy. This gave a rise in real GDP growth by 3.0 percentage points over the following year and a half, starting in Q1 of 2009.

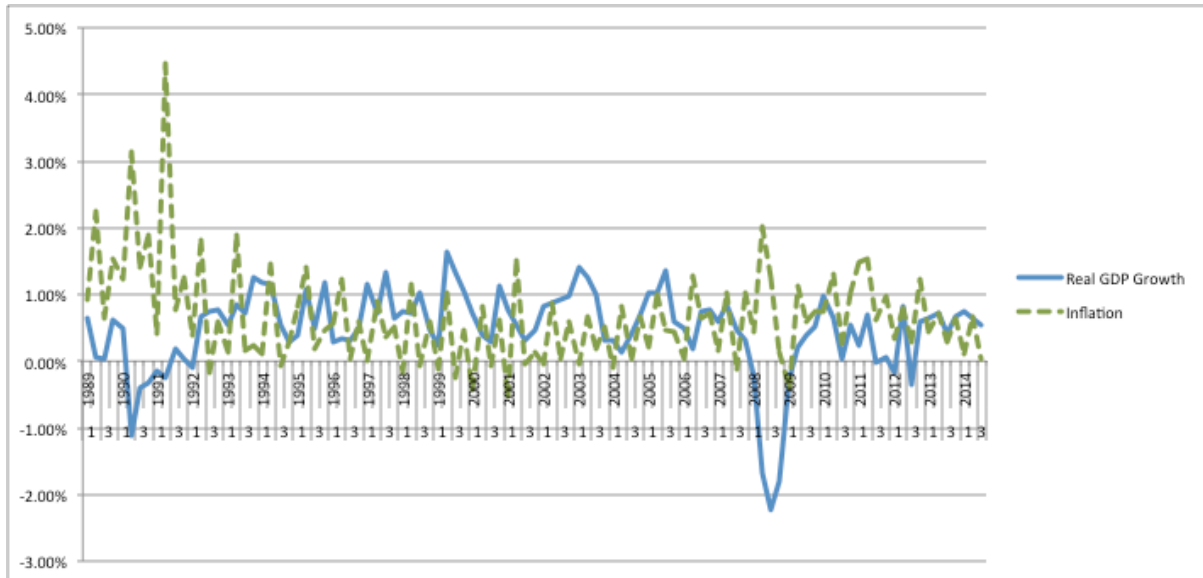


Figure 2. Inflation and Real GDP Growth

The chart shows the second explanatory variable, the Consumer Price Index percentage rate, as a measure of inflation based on the 2005 GBP prices. The dependent variable is the real GDP growth rate change (in percentage) from the period of 1989:1 to 2014:3

The relationship between the inflation and the real GDP growth shown above is hard to make out, but as it appears as there is a negative relationship between the variables. If we look at the start of 1989 we can see a rise in inflation while the GDP growth drops, and then the inverted effect during the middle and end of 1989. This shows the effect of the inflation variable, that when the growth of the GDP is down stimulus of the monetary policy gives a rise in inflation which in turn increase the growth. This is very much a simplification of the relationship, but the casual view of the both variables brings some light of their interactions.

4.2 Regression Results

<i>k</i> Quarters Ahead	β_0	β_1	Adjust. R^2	SEE	F-statistic	Prob.
1	0.019 (0.004)	0.605** (0.227)	0.087	0.024	10.827	0.001
2	0.019 (0.004)	0.649** (0.231)	0.123	0.021	15.332	0.000
3	0.019 (0.004)	0.673** (0.231)	0.151	0.020	19.014	0.000
4	0.019 (0.003)	0.682** (0.232)	0.177	0.018	22.469	0.000
5	0.019 (0.003)	0.682** (0.224)	0.199	0.017	25.524	0.000
6	0.019 (0.003)	0.660** (0.199)	0.208	0.016	26.727	0.000
7	0.019 (0.003)	0.608** (0.186)	0.196	0.015	24.649	0.000
8	0.020 (0.003)	0.550** (0.176)	0.177	0.015	21.587	0.000
16	0.021 (0.002)	0.331** (0.114)	0.117	0.012	12.492	0.001

Table 1. In-sample regression results (model 1)

The table shows the regression results of model 1, which is computed as following:

$$\text{Cumulative change} = (400/k)[\log(y_{t+k}/y_t)] = \beta_0 + \beta_1 \text{SPREAD}_t + u_t$$

Model 1 uses a single independent variable, the yield spread of the 5-year UK Treasury bond and the 6-month UK Treasury bill. β_0 is the coefficient of the intercept and β_1 is the coefficient of the spread of the yields over the period 1989:1 to 2014:3.

** Statistically different from zero at a 5% level.

In parenthesis are the Newey and West (1987) standard errors that take the moving average effect of the forecasting horizons into account.

The table above shows the regression results of our first model, containing the dependent variable of the cumulative GDP change in the UK, and the yield difference between the 5-year UK Treasury bond and the 6-month UK Treasury bill. The table displays the number of quarters ahead, the coefficients β_0 and β_1 , the intercept coefficient of the constant and the coefficient of the yield spread. These coefficient are then evaluated, first by the adjusted R-squared, which can be interpreted as proportion of total variation in the dependent variable explain by the independent variables. Secondly we look at the standard error of the estimation (SEE), which is the standard deviation of the prediction errors.

Then we have the F-statistic that is the ration of the mean regression sum of squares divided by the mean error sum of squares, and finally the probability (Prob) of the regression coefficient of being zero, in other words a hypothesis testing of the coefficient. As we can see from the regression all of our variables are statistically significant at a 5% level for all quarters. The explanatory power increases with the numbers of quarters ahead, until quarter 7 when the R-squared decreases, which is consistent with previous research (Bonser-Neal and Morley, 1997). In other words, this means that the future economic activity of the UK can be explained to up to 20.8% by the single economic variable, the yield spread, 6 quarters ahead.

<i>k</i> Quarters Ahead	β_0	β_1	β_2	Adjust. R^2	SEE	F-statistic	Prob.
1	0.037 (0.004)	0.164 (0.194)	-0.633** (0.126)	0.233	0.022	16.522	0.000
2	0.035 (0.004)	0.258 (0.215)	-0.566** (0.126)	0.265	0.019	19.227	0.000
3	0.033 (0.005)	0.331 (0.245)	-0.497** (0.138)	0.277	0.018	20.199	0.000
4	0.031 (0.006)	0.389 (0.272)	-0.429** (0.159)	0.285	0.017	20.703	0.000
5	0.030 (0.006)	0.429 (0.267)	-0.371** (0.166)	0.290	0.016	21.060	0.000
6	0.029 (0.006)	0.436* (0.257)	-0.330* (0.169)	0.291	0.015	20.865	0.000
7	0.028 (0.006)	0.404* (0.241)	-0.302* (0.165)	0.273	0.015	19.050	0.000
8	0.027 (0.006)	0.366 (0.225)	-0.273* (0.160)	0.247	0.014	16.556	0.000
16	0.022 (0.005)	0.299* (0.168)	-0.042 (0.128)	0.109	0.012	6.332	0.000

Table 2. In-sample regression results (model 2)

The table shows the regression results of model 2, which is computed as following:

$$\text{Cumulative change} = (400/k)[\log(y_{t+k}/y_t)] = \beta_0 + \beta_1 \text{SPREAD}_t + \beta_2 \text{CPI}_t + u_t$$

Model 2 uses multiple independent variables, the yield spread of the 5-year UK Treasury bond and the 6-month UK Treasury bill and the seasonally adjusted consumer price index as a measure of inflation. β_0 is the intercept, β_1 is the spread of the yields and β_2 is the seasonally adjusted CPI. Period 1989:1 to 2014:3.

** Statistically different from zero at a 5% level.

* Statistically different from zero at a 10% level.

In parenthesis are the Newey and West (1987) standard errors that take the moving average effect of the forecasting horizons into account.

Our second model contains both the independent variable of the yield spread of the 5-year UK Treasury bond and the 6-month UK Treasury bill, and the seasonally adjusted CPI as our second variable. The model looks as following:

$$\text{Cumulative change} = (400/k)[\log(y_{t+k}/y_t)] = \beta_0 + \beta_1 SPREAD_t + \beta_2 CPI_t + u_t$$

The β_i coefficients represent the change in the variables that would occur with a 1% change in the dependent variable of the GDP. Both the coefficient of the constant, β_0 , and the coefficient of the yield spread are positive, which is consistent with previous research on how the yield spread has a predictive power of future economic outcome (Estrella and Hardeouvelis, 1991). In our case the coefficient of the CPI as a measure of inflation is shown to be negative for all quarters, which can partly be explained by a very volatile inflation in which the inflation effect can show a positive effect on the growth a few quarters ahead. Our CPI data is only quarterly seasonally adjusted without any lags (Bruno and Easterly, 1998). As previous research suggest the predictive powers of the yield spread are best shown after couple of quarters ahead (preferably a year), and this is also shown in our table where the coefficient of the yield spread increases the further horizon. This is in parallel to the CPI coefficient where this one decreases the further horizon. Our first explanatory variable, the yield spread, shows statistical significance at a 10% level during quarter 6,7 and 16, proving the increasing effect of the yield spread of an extended horizon. The second explanatory variable, the CPI, has a statistical significant high coefficient value from quarter one to quarter five, whereas the significance and the coefficient values decrease for the remaining quarters.

4.1.1 Hypothesis testing (F-test)

As all we know now is that there is a relationship between the dependent variable and the explanatory variables, but we do not know if it reflects a true and significant relationship between the variables. To find out if the relationship is not just based on chance we will perform a *F-test of goodness of fit*. This is conducted by creating a null hypothesis $H_0: \beta_i = 0$, where $i = 1,2$, that there is no relationship between the dependent and the explanatory variables. Then we create a true-hypothesis: $H_1: \beta_i \neq 0$, all tested at a 5% significance level, so if the probability value of the F-statistic in our regression result exceeds 5% the we must accept the null hypothesis, and if not we can reject it. Rejecting the null hypothesis would

mean that our explanatory variables have a significant and true relationship to our dependent variable. Although this method is not error free, since it opens up to the risk of making a Type I error, meaning to reject the null hypothesis when it is true which is bound to happen at 5% of the times (Dougherty, 2011). That is why we in this case perform our F-tests at a 1% level, concluding that model 1 is significant at both a 5% and a 1% level, which means that the null hypothesis is rejected and that at least one of the explanatory variables is not equal to zero.

To test model 2 where we have two explanatory variables, we test the variables one at a time to establish their individual impact on the dependent variable. First we can see the spread variable that in model 2 only has significance on a 10% level during quarter 6,7 and 16, but as a single variable in model 1 has significance on a 5% level during all of the quarters. Our second variable inflation has significance on a 5% level during quarters 1 to 5, and significance at a 10% level during quarters 6 to 8. Since the inflation coefficient β_2 is negative throughout the horizon, model 2 shows less significance than expected, this may possibly be due to delayed economic impact of increased/decreased inflation and a non-lagged CPI variable.

4.2 Forecast model

4.2.1 Out-of-sample forecasting results

The table below shows the out-of-sample forecasting results for model 1 and model 2. These are computed using a static forecasting model, where the one-step-ahead value is based on the previous value.

$$\text{Forecasting error} = y_{t,t+k}^c - \hat{y}_{t,t+k}^c$$

Whereas $y_{t,t+k}^c$ denotes the actual cumulative growth:

$$y_{t,t+k}^c = \beta_0 + \beta_1 SPREAD_t + \beta_2 CPI_t + u_t$$

And $\hat{y}_{t,t+k}^c$ denotes the forecasted values based on the in-sample-regression:

$$\hat{y}_{t,t+k}^c = \hat{\alpha}_F + \hat{\beta}_F y_{t,t+k}^c + u_t$$

Forecasting Horizon; <i>k</i> Quarters Ahead	Model 1			Model 2		
	Intercept $\hat{\alpha}_F$	Coefficient $\hat{\beta}_F$	Adjust. R^2	Intercept $\hat{\alpha}_F$	Coefficient $\hat{\beta}_F$	Adjust. R^2
1	-0.020 (-1.021)	1.409* (1.864)	0.121	-0.001 (-0.138)	0.944* (1.958)	0.143
2	-0.009 (-0.694)	0.945* (1.950)	0.141	-0.009 (-1.721)	1.289* (4.890)	0.589
3	0.001 (0.096)	0.554 (1.123)	0.016	-0.013 (-2.235)	1.442** (5.119)	0.627
4	0.014 (1.134)	0.041 (0.086)	-0.071	-0.012 (-1.549)	1.337** (3.641)	0.467
5	0.020 (1.683)	-0.231 (-0.486)	-0.058	-0.003 (-0.288)	0.886 (1.694)	0.126
6	0.029 (2.641)	-0.610 (-1.386)	0.066	0.012 (0.978)	0.134 (0.230)	0.086
7	0.034 (3.361)	-0.844* (-2.050)	0.211	0.023 (1.899)	-0.397 (-0.697)	-0.049
8	0.036 (3.915)	-0.960** (-2.521)	0.327	0.030 (2.856)	-0.742 (-1.499)	0.111
16	0.025 (1.953)	-0.345 (-0.685)	-0.362	0.026 (1.946)	-0.386 (-0.727)	-0.308

Table 3. Out-of-sample forecast results (model 1&2)

The table shows the forecast results of model 1 and 2 with the sample period 2009:3 to 2014:3 based on the regression results of the period 1989:1 to 2009:2. Intercept $\hat{\alpha}_F$ and the coefficient $\hat{\beta}_F$ denote the coefficient of the constant and the coefficient of the explanatory variable of the forecast sample of cumulative GDP growth. The adjusted R^2 denotes the explanatory power of the forecasted GDP change compared to the actual GDP change within the sample.

** Statistically different from zero at a 5% level.

* Statistically different from zero at a 10% level.

T-statistics in parenthesis

The table values are retrieved from an Eviews regression, on a forecasted GDP growth data sample between 2009 Q3 through 2014 Q3, and the actual GDP growth. The intercept $\hat{\alpha}_F$ is the constant coefficient of the forecast, and the coefficient $\hat{\beta}_F$ is the explanatory variable of the forecasted GDP growth. As we can see in model 1, containing only the explanatory variable of the yield spread of the 5-year and the 6-month UK Treasury securities, $\hat{\beta}_F$ holds significance, although at a 10% level, during quarter 1, 2 and 7 but only remains positive during quarter 1 to 4. At quarter 8 the forecasted coefficient value holds a significance of 5% and although the coefficient is negative, the R-squared value is at 32.7% which accounts for almost one-third of the actual GDP movement. In model 2, which contains both the yield spread-variable and the inflation-variable, we can see a higher explanatory power of the coefficient but in a negative capacity, whereas the horizon of one quarter is significant at a 10% level and the following 3 quarters hold significance at a 5% level. Needless to say, model 2 has higher coefficient values, indicating a bigger movement in the forecasted GDP growth with a 1% change in the actual GDP growth.

Even if the table shows some values of some of the horizon quarters that hold significance for the dependent variable, we do not know if this is a true relationship. To test the relationship and the actual performance of the forecast we turn to the t-statistics, shown in parenthesis in table. The t-statistic is the estimated value of the variable divided by its standard errors, so the larger t-statistic value the less chance of the coefficient value of being zero and thereby have no relationship with the dependent variable. So if we look at the table, we can see that the $\hat{\beta}_F$ -values with the highest t-statistics is also the ones having the most significance, e.g. the third quarter horizon in model 2 bears the highest t-statistic value (5.119) and is therefore the forecast horizon with the highest reliability.

Let us now perform a hypothesis testing of the coefficients to see if our forecasted model holds significance at any of the forecasted horizons. Since we know that the intercept $\hat{\alpha}_F$ is the coefficient of the entry point of which the forecasted model starts, a good value of this coefficient would be *zero* since we want the forecasted cumulative GDP growth to have the same intercept as the actual cumulative GDP growth. The coefficient $\hat{\beta}_F$ should, if a strong model, move 1% if the movement in the dependent variable moves 1%, therefore should the $\hat{\beta}_F$ have the value of *one* in our hypothesis testing (Estrella and Hardouvelis, 1991).

$$H_0: \hat{\alpha}_F = 0$$

$$H_1: \hat{\alpha}_F \neq 0$$

In model one; consisting of one independent variable - the yield spread, we can reject the null hypothesis only during quarter horizon 7 and 8. In model 2 the null hypothesis is rejected at a horizon of 3 quarters and 8 quarters, that is that the chance of an alpha value of zero is statistically significant at a 5% level.

$$H_0: \hat{\beta}_F = 1$$

$$H_1: \hat{\beta}_F \neq 1$$

The null hypothesis for the $\hat{\beta}_F$ can only be rejected for model 1 during quarters 7 and 8, which is consistent with the hypothesis for $\hat{\alpha}_F$. Model 2 rejects the null hypothesis for the horizon quarter 7 and 8, whereas the quarter 8 also rejects the null hypothesis for coefficient α_F .

4.2.2 Root Mean Squared Error model

While using hypothesis testing on the forecasted coefficients $\hat{\alpha}_F$ and $\hat{\beta}_F$, there is always a risk at our chosen level of 5% to get a false positive or as it is called a Type 1 error, meaning to reject a true null hypothesis. Although our previous models show some significant results for some of the forecasted quarter horizons, we will look at another evaluation tool to determine the accuracy of the forecasting. The Root Mean Squared Error model (*RMSE*) provides an estimation of the out-of-sample forecast error. The lower the RMSE, the better the forecast, and one of the advantages of using this measurement is the comparability of including different variables in ones forecasting model (Bonser-Neal and Morley, 1997). The *RMSE* measures the difference of the average error in the actual model, in our case the cumulative GDP growth, to the forecasted average error of the cumulative GDP growth given as squared root of the mean sum of squared errors, both for model 1 and model 2.

$$RMSE = \sqrt{\frac{1}{T} \sum_{t=1}^T (\hat{y}_{t,t+k}^c - y_{t,t+k}^c)^2}$$

The RMSE model is explained as $y_{t,t+k}^c$ is the actual GDP growth, $\hat{y}_{t,t+k}^c$ is the predicted value of the GDP growth and T is the number of out-of-sample forecasts.

4.2.3 Theil Coefficient

The Theil Coefficient is another measure of the forecasts accuracy; its output is the inequality between the actual value and the forecasted value, measured as the 1 for the worst possible outcome and 0 as the best and most accurate forecast (zero inequality between actual and forecasted value) (Leuthold, 1975). The advantage of the model mostly lies in the ability to use any measurements in the variables since the coefficient explains the inequality as a percentage point between 1.000 and 0.000, this makes the Theil coefficient a good complement in evaluating the forecasted models.

$$U = \frac{\sqrt{\frac{1}{T} \sum (y_{t,t+k}^c - \hat{y}_{t,t+k}^c)^2}}{\sqrt{\frac{1}{T} \sum \hat{y}_{t,t+k}^c{}^2 + \frac{1}{T} \sum y_{t,t+k}^c{}^2}}$$

The U -coefficient takes a value between zero and one. As previous $y_{t,t+k}^c$ represents the actual GDP growth, $\hat{y}_{t,t+k}^c$ the forecasted value of the GDP growth and T is the number of out-of-sample forecasts.

Forecasting Horizon; <i>k</i> Quarters Ahead	Model 1			Model 2		
	RMSE	Adjust. R^2	Theil Coefficient (U)	RMSE	Adjust. R^2	Theil Coefficient (U)
1	0.016	0.121	0.342	0.013	0.143	0.304
2	0.013	0.141	0.302	0.007	0.589	0.176
3	0.013	0.016	0.310	0.007	0.627	0.174
4	0.014	-0.071	0.326	0.007	0.467	0.191
5	0.014	-0.058	0.340	0.009	0.126	0.223
6	0.015	0.066	0.357	0.009	-0.086	0.250
7	0.015	0.211	0.366	0.010	0.049	0.264
8	0.014	0.327	0.367	0.010	0.111	0.266
16	0.009	-0.362	0.223	0.009	-0.308	0.216

Table 4. Root Mean Squared Error model - Out-of-sample forecasting

The table shows the *Root Mean Squared Error model (RMSE)* results along with the *Adjusted- R^2* and the *Theil coefficient* for the forecasting horizon of quarter 1 to 16. The forecasted sample is between 2009:3 to 2014:3 based on the sample period of 1989:1 to 2009:2 and is performed on model 1, containing the yield-spread as an explanatory variable, and model 2 which contains both the yield-spread and the inflation variable. The lowest two values of the RMSE and the Theil-coefficient are shown in bold.

Model 1 shows lower RMSE for the second and third quarter that in previous forecast results show significance for the value of quarter 2. The lowest RMSE is for quarter 16, which is not conclusive compared to earlier results. For model 2 the RMSE shows the lowest values between quarter 2 and 4, which is conclusive compared to earlier predictive results. If we look at the Theil coefficient the values for both model 1 and 2 overlaps the RMSE results, where the lowest values in model 1 is for quarter 2 and 16, and quarter 2 and 3 for model 2.

5. ANALYSIS

From the regressions for both model 1 and model 2 we can clearly see that there is a significant relationship between the independent variables, yield spread and inflation, and the dependent variable, the cumulative GDP growth for the economy in the United Kingdom between the sample periods of 1989:1 to 2014:3. These in-sample results show that the relationship is significant at a 5% level of confidence for all quarters ahead in model 1, and can explain the total movement of the dependent variable up to 20.8%. In model 2 the inflation variable shows some further explanatory power and even makes the spread-coefficient unnecessary during certain quarters. Although during quarter 7, with both variables significant, the total variation of the dependent variable can be explained by 29.1%.

Once the relationship has been established, we move on to perform an out-of-sample forecast for the last 5 years of the sample (2009:3 to 2014:3) based on the previous 20 years and a quarter (1989:1 to 2009:2). This results in a forecasted estimation of the cumulative GDP growth for the final 5 years, which is then compared to the actual values of the cumulative GDP growth for the final 5 years. The forecast is significant for model 1 in both quarter 1, 2 and 7,8, and significant in model 2 for quarters 1 to 4. When hypothesis testing the intercept variable and the coefficient variable, model 1 show statistical significance of the forecasting model for quarter 7 and 8, which is consistent with previous discoveries. For model 2 the only quarter that can reject the null hypothesis (for α_F equals zero and β_F equals one) is quarter 8, which is not consistent with the significance of the variable and makes the answer inconclusive.

We also look at the Root Mean Squared Errors and the Theil coefficient to further investigate the goodness of fit of our forecasted models. The *RMSE* model measures the average errors in both the forecasted samples and the actual samples for both models; same as the Theil coefficient that measures the inequality between the values in a matter of percentage, the lower the percentage the better the fit. Model 1 shows lowest values of RMSE during quarter 2,3 and 16, and the lowest Theil values during quarter 2 and 16, which in this case is inconclusive compared to earlier results. Model 2 shows lowest RMSE values during quarter 2,3,4 and 16 and Theil values during quarter 2 and 3, where quarter 3 is significant for β_F hypothesis.

In this case the model shows evidence that the forecast of model 2 during quarter 3 is significant, although if we look back only the inflation variable is significant at a 5% level during quarter 3.

6. CONCLUSION & FUTURE RESEARCH

The aim of this paper has been to investigate the ability to predict future economic movements based on the forecasting powers of the interest rate spread (or yield) and the consumer price index, as a measure of inflation in the United Kingdom. To perform this task I have been using the yield spread of the 5-year UK Treasury bond and the 6-month UK Treasury bill, seasonally adjusted quarterly data of the UK CPI and seasonally adjusted quarterly data of the UK GDP. Multiple regression models of both model 1, containing only the yield spread as an explanatory variable, and model 2, containing both the yield spread and inflation as explanatory variables, have been performed. These in-sample results have shown that the yield spread on its own, during all 16 quarters-ahead, have statistical significance and positive relationship with the cumulative GDP growth, and can explain as much as 20.8% of the total movement in the GDP. By adding the inflation variable the significance of the yield spread drops and inflation is shown to have a negative, yet still significant, relationship with the GDP growth. The negative relationship of the CPI and the GDP variable might be a result of non-lagged CPI variable, as inflation stimulation might have a delayed economic impact.

The out-of-sample forecast shows that both model 1 and 2 have some predictive power of the future economic variation over different quarters. This is consistent with previous research on the subject of out-of-sample forecasting outside the United States. In an economic review from 1997, it is shown that the forecasted GDP variation on a horizon of 1-year explains roughly 20% of the actual GDP variation based on the yield spread in the United Kingdom (Bonser-Neal and Morley, 1997). This paper have concluded that the GDP variation can be explain by 12-14% during quarter 1 and 2, and up to 21-32% during quarter 7 and 8 for model 1. In the second model the predictive power increases radically during the first quarters, showing explanatory powers of up to 62.7%. Although these first quarters are not significant, and can partly be explained by a high volatility in the CPI, only 2 years of forecast horizon shows significance and explains the GDP movement by 11%, but this result is not statistically significant and therefore inconclusive. As for the scope of this paper, is has

shown that the yield spread on its own has strong relations and certain predictive powers in forecasting GDP movement, with an R^2 value of roughly 20%. Although the forecasting abilities have shown only a few statistically significant quarters, all these for model 1 with the highest significance for forecasting 1 year and a quarter ahead. Model 2 shows the same result when performing hypothesis testing for the coefficient and looking at the RMSE- and Theil values, although some of these values contradict each other making the result inconclusive.

Overall this paper has shown that the predictive powers of both the financial variable of the term structure spread and the monetary variable of inflation have strong relations to the movement of the GDP and some forecasting abilities. The forecasting abilities should have, according to older research on this subject, have stronger explanatory power but as we progress into the future more variables, not only domestic variables, play a part in the interest rate decisions. This results in more noise and less explanatory power out of one single variable.

To investigate the power of economic prediction further, one might consider updating the out-of-sample variables, and extend the sample as we move into the future to see if the significance of the single financial variable will continue to decrease. A greater data sample has been proved to increase the prediction power, so this might work in the other direction of decreasing significance of single financial variables. Further research might also include more macroeconomic and financial variables to get a better forecasting result.

7. REFERENCES

Published Sources

Bonser-Neal Catherine, Morley Timothy (1997), "Does the Yield spread Predict Real Economic Activity? A Multicountry Analysis", Federal Reserve Bank of Kansas City *Economic Review*, Vol. 82

Bruno Michael, Easterly William (1998), "Inflation Crises and Long-Run Growth", Journal of Monetary Economics *The World Bank Washington*, Vol. 3-26

Dotsey Michael (1998), "The Predictive Content of the Interest Rate Term Spread for Future Economic Growth", Economic Quarterly *Federal Reserv Bank of Richmond*, Vol. 84

Estrella Arturo, Hardeouvelis Gikas (1991), "The Term Structure as a Predictor of Real Economic Activity", *The Journal of Finance*, Vol. 46

Estrella Arturo, Mishkin S. Frederic (1997), "Predicting U.S. Recessions: Financial Variables as Leading Indicators", *The Review of Economics and Statistics*, Vol. 80

Estrella Arturo, Trubin Mary (2006), "The Yield Curve as a Leading Indicator: Some Practical Issues", *Current issues in Economics and Finance Federal Reserve Bank of New York*, Vol. 12

Hamilton James, Kim Dong Heon (2000), "A re-examination of the predictability of economic ativity using the Yield Spread", National Bureau of Economic Research *NBER Working Paper Series*, Vol. 7954

Kahn Mohsin, Senhadji Abdelhak (2000), "The Threshold Effects in the Relationship Between Inflation and Growth", IMF Working Papers *IMF Institute*, Vol 110

Leuthold Raymond (1975), " On the Use of Theil's Inequality Coefficients", *American Journal of Agricultural Economics AAEA*, Vol. 57

Litterman Robert, Scheinkman José (1991), "Common Factors Affecting Bond Returns", *The Journal of Fixed Income Goldman Sachs*, June 1991

Smets Frank, Tsatsaronis Kostas (1997), "Why does the Yield Curve Predict Economic Activity?", Working Papers *Bank for International Settlements*, No. 49

Zhang Dalu, Moffatt Peter (2012), "The yield curve as a leading indicator in economic forecasting in the UK", University of East Anglia Applied and Financial Economics *Working Paper Series*, Vol. 035

Literature Sources

Dougherty Christopher (2011), "Introduction to Econometrics", *Oxford*, Fourth Edition

Stander S. Yolanda (2005), "Yield Curve Modeling", Palgrave McMillan

Internet Sources

www.bankofengland.co.uk

www.datastream.com

www.investopedia.com

www.research.stlouisfed.org

8. APPENDIX

8.1 Regression Raw Data

	GDP	Spread	CPI		GDP	Spread	CPI
1989-01-01	261846000000	-0.028	56.985	2002-01-01	348115000000	0.010	82.638
1989-04-01	263514000000	-0.029	58.266	2002-04-01	350978000000	0.010	83.366
1989-07-01	263651000000	-0.034	58.645	2002-07-01	354058000000	0.007	83.395
1989-10-01	263719000000	-0.039	59.547	2002-10-01	357286000000	0.006	83.890
1990-01-01	265371000000	-0.031	60.275	2003-01-01	360733000000	0.004	83.861
1990-04-01	266644000000	-0.026	62.168	2003-04-01	365803000000	0.004	84.414
1990-07-01	263704000000	-0.028	63.041	2003-07-01	370428000000	0.007	84.560
1990-10-01	262665000000	-0.022	64.235	2003-10-01	374127000000	0.008	84.997
1991-01-01	261838000000	-0.023	64.497	2004-01-01	375324000000	0.005	84.909
1991-04-01	261442000000	-0.010	67.380	2004-04-01	376455000000	0.004	85.608
1991-07-01	260779000000	-0.006	67.904	2004-07-01	376942000000	0.001	85.637
1991-10-01	261240000000	-0.007	68.749	2004-10-01	378470000000	-0.002	86.220
1992-01-01	261346000000	-0.009	69.011	2005-01-01	381142000000	-0.002	86.394
1992-04-01	261067000000	-0.009	70.263	2005-04-01	385058000000	-0.004	87.268
1992-07-01	262816000000	-0.009	70.146	2005-07-01	389023000000	-0.002	87.676
1992-10-01	264742000000	0.003	70.554	2005-10-01	394268000000	-0.002	88.054
1993-01-01	266762000000	0.007	70.641	2006-01-01	396566000000	-0.002	88.083
1993-04-01	268180000000	0.010	71.981	2006-04-01	398553000000	0.001	89.219
1993-07-01	270418000000	0.006	72.097	2006-07-01	399251000000	-0.001	89.801
1993-10-01	272389000000	0.005	72.272	2006-10-01	402258000000	-0.003	90.442
1994-01-01	275836000000	0.009	72.359	2007-01-01	405329000000	-0.003	90.587
1994-04-01	279116000000	0.023	73.408	2007-04-01	407767000000	-0.003	91.519
1994-07-01	282336000000	0.024	73.349	2007-07-01	411205000000	-0.009	91.403
1994-10-01	283840000000	0.019	73.553	2007-10-01	413131000000	-0.013	92.335
1995-01-01	284637000000	0.014	74.165	2008-01-01	414424000000	-0.013	92.742
1995-04-01	285751000000	0.010	75.213	2008-04-01	413465000000	-0.011	94.606
1995-07-01	288862000000	0.007	75.359	2008-07-01	406584000000	-0.012	95.800
1995-10-01	290247000000	0.005	75.708	2008-10-01	397522000000	-0.008	95.916
1996-01-01	293666000000	0.009	76.145	2009-01-01	390406000000	0.007	95.538
1996-04-01	294490000000	0.015	77.077	2009-04-01	389388000000	0.014	96.615
1996-07-01	295521000000	0.013	77.106	2009-07-01	390167000000	0.020	97.197
1996-10-01	296474000000	0.007	77.572	2009-10-01	391685000000	0.020	97.925
1997-01-01	297909000000	0.005	77.572	2010-01-01	393678000000	0.021	98.653
1997-04-01	301318000000	0.003	78.270	2010-04-01	397525000000	0.015	99.934
1997-07-01	303490000000	-0.004	78.562	2010-07-01	400096000000	0.010	100.197
1997-10-01	307560000000	-0.010	78.969	2010-10-01	400195000000	0.009	101.216
1998-01-01	309517000000	-0.011	78.824	2011-01-01	402341000000	0.014	102.730
1998-04-01	311857000000	-0.014	79.726	2011-04-01	403260000000	0.011	104.302
1998-07-01	314098000000	-0.017	79.668	2011-07-01	406068000000	0.001	104.943
1998-10-01	317295000000	-0.017	80.134	2011-10-01	406008000000	0.000	105.962
1999-01-01	318806000000	-0.008	80.047	2012-01-01	406283000000	-0.002	106.311
1999-04-01	319560000000	-0.002	80.862	2012-04-01	405560000000	-0.004	107.156
1999-07-01	324767000000	0.003	80.658	2012-07-01	408938000000	-0.003	107.476
1999-10-01	329111000000	0.001	81.037	2012-10-01	407557000000	0.001	108.786
2000-01-01	332555000000	-0.001	80.687	2013-01-01	409985000000	0.003	109.252
2000-04-01	334960000000	-0.005	81.357	2013-04-01	412620000000	0.004	110.039
2000-07-01	336221000000	-0.005	81.299	2013-07-01	415577000000	0.010	110.359
2000-10-01	337211000000	-0.006	81.794	2013-10-01	417265000000	0.010	111.058
2001-01-01	341026000000	-0.003	81.357	2014-01-01	420091000000	0.013	111.174
2001-04-01	343637000000	0.001	82.580	2014-04-01	423249000000	0.014	111.931
2001-07-01	345468000000	0.004	82.551	2014-07-01	426022000000	0.013	111.960
2001-10-01	346546000000	0.008	82.667	2014-10-01	428347000000	0.008	112.077

8.2 In-sample Regressions

Regression results of model 1, using the single explanatory variable of the yield spread.

Dependent Variable: Y1				
Method: Least Squares				
Date: 05/07/15 Time: 17:11				
Sample: 1 105				
Included observations: 104				
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.019047	0.003734	5.101224	0.0000
X1	0.604548	0.227113	2.661883	0.0090
R-squared	0.095960	Mean dependent var	0.018930	
Adjusted R-squared	0.087097	S.D. dependent var	0.024631	
S.E. of regression	0.023534	Akaike info criterion	-4.641735	
Sum squared resid	0.056490	Schwarz criterion	-4.590885	
Log likelihood	243.3704	Hannan-Quinn criter.	-4.621137	
F-statistic	10.82687	Durbin-Watson stat	0.748352	
Prob(F-statistic)	0.001374	Wald F-statistic	7.085621	
Prob(Wald F-statistic)	0.009029			

Dependent Variable: Y2				
Method: Least Squares				
Date: 05/07/15 Time: 17:25				
Sample: 1 105				
Included observations: 103				
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.019092	0.003616	5.279808	0.0000
X1	0.649464	0.230821	2.813719	0.0059
R-squared	0.131795	Mean dependent var	0.018885	
Adjusted R-squared	0.123199	S.D. dependent var	0.022572	
S.E. of regression	0.021136	Akaike info criterion	-4.856478	
Sum squared resid	0.045119	Schwarz criterion	-4.805318	
Log likelihood	252.1086	Hannan-Quinn criter.	-4.835756	
F-statistic	15.33196	Durbin-Watson stat	0.384458	
Prob(F-statistic)	0.000164	Wald F-statistic	7.917015	
Prob(Wald F-statistic)	0.005887			

Dependent Variable: Y3				
Method: Least Squares				
Date: 05/21/15 Time: 18:33				
Sample: 1 105				
Included observations: 102				
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.019208	0.003494	5.497983	0.0000
X1	0.673240	0.232660	2.893658	0.0047
R-squared	0.159763	Mean dependent var	0.018900	
Adjusted R-squared	0.151361	S.D. dependent var	0.021221	
S.E. of regression	0.019553	Akaike info criterion	-5.011957	
Sum squared resid	0.038232	Schwarz criterion	-4.960487	
Log likelihood	257.6095	Hannan-Quinn criter.	-4.991111	
F-statistic	19.01407	Durbin-Watson stat	0.288301	
Prob(F-statistic)	0.000032	Wald F-statistic	8.373257	
Prob(Wald F-statistic)	0.004674			

Dependent Variable: Y4				
Method: Least Squares				
Date: 05/07/15 Time: 17:14				
Sample: 1 105				
Included observations: 101				
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.019325	0.003373	5.729700	0.0000
X1	0.681617	0.232331	2.933822	0.0042
R-squared	0.184976	Mean dependent var	0.018926	
Adjusted R-squared	0.176743	S.D. dependent var	0.019964	
S.E. of regression	0.018114	Akaike info criterion	-5.164683	
Sum squared resid	0.032483	Schwarz criterion	-5.112898	
Log likelihood	262.8165	Hannan-Quinn criter.	-5.143719	
F-statistic	22.46882	Durbin-Watson stat	0.206861	
Prob(F-statistic)	0.000007	Wald F-statistic	8.607312	
Prob(Wald F-statistic)	0.004161			

Dependent Variable: Y5				
Method: Least Squares				
Date: 05/07/15 Time: 17:15				
Sample: 1 105				
Included observations: 100				
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.019386	0.003264	5.939463	0.0000
X1	0.681517	0.223505	3.049226	0.0030
R-squared	0.206632	Mean dependent var	0.018913	
Adjusted R-squared	0.198537	S.D. dependent var	0.018905	
S.E. of regression	0.016928	Akaike info criterion	-5.299911	
Sum squared resid	0.028082	Schwarz criterion	-5.247807	
Log likelihood	266.9955	Hannan-Quinn criter.	-5.278824	
F-statistic	25.52408	Durbin-Watson stat	0.166287	
Prob(F-statistic)	0.000002	Wald F-statistic	9.297777	
Prob(Wald F-statistic)	0.002950			

Dependent Variable: Y6				
Method: Least Squares				
Date: 05/07/15 Time: 17:15				
Sample: 1 105				
Included observations: 99				
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.019435	0.002918	6.661218	0.0000
X1	0.660399	0.198675	3.324011	0.0013
R-squared	0.216013	Mean dependent var	0.018908	
Adjusted R-squared	0.207931	S.D. dependent var	0.017951	
S.E. of regression	0.015976	Akaike info criterion	-5.415442	
Sum squared resid	0.024758	Schwarz criterion	-5.363015	
Log likelihood	270.0644	Hannan-Quinn criter.	-5.394230	
F-statistic	26.72657	Durbin-Watson stat	0.129391	
Prob(F-statistic)	0.000001	Wald F-statistic	11.04905	
Prob(Wald F-statistic)	0.001253			

Dependent Variable: Y7				
Method: Least Squares				
Date: 05/07/15 Time: 17:16				
Sample: 1 105				
Included observations: 98				
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.019496	0.002841	6.861872	0.0001
X1	0.608235	0.186178	3.266957	0.0014
R-squared	0.204304	Mean dependent var	0.018987	
Adjusted R-squared	0.196016	S.D. dependent var	0.017071	
S.E. of regression	0.015311	Akaike info criterion	-5.500231	
Sum squared resid	0.022506	Schwarz criterion	-5.447471	
Log likelihood	271.5115	Hannan-Quinn criter.	-5.478891	
F-statistic	24.64910	Durbin-Watson stat	0.110721	
Prob(F-statistic)	0.000003	Wald F-statistic	10.6730	
Prob(Wald F-statistic)	0.001508			

Dependent Variable: Y8				
Method: Least Squares				
Date: 05/07/15 Time: 17:16				
Sample: 1 105				
Included observations: 97				
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.019563	0.002778	7.042209	0.0000
X1	0.550177	0.175655	3.132147	0.0023
R-squared	0.185161	Mean dependent var	0.019076	
Adjusted R-squared	0.176584	S.D. dependent var	0.016301	
S.E. of regression	0.014792	Akaike info criterion	-5.569050	
Sum squared resid	0.020786	Schwarz criterion	-5.515963	
Log likelihood	272.0989	Hannan-Quinn criter.	-5.547584	
F-statistic	21.58744	Durbin-Watson stat	0.100080	
Prob(F-statistic)	0.000011	Wald F-statistic	9.810342	
Prob(Wald F-statistic)	0.002307			

Dependent Variable: Y16				
Method: Least Squares				
Date: 05/08/15 Time: 09:58				
Sample (adjusted): 1 88				
Included observations: 88 after adjustments				
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.020874	0.002385	8.751012	0.0000
X1	0.331381	0.113574	2.917765	0.0045
R-squared	0.126834	Mean dependent var	0.020462	
Adjusted R-squared	0.116681	S.D. dependent var	0.012287	
S.E. of regression	0.011548	Akaike info criterion	-6.062224	
Sum squared resid	0.011468	Schwarz criterion	-6.005921	
Log likelihood	268.7378	Hannan-Quinn criter.	-6.039541	
F-statistic	12.49212	Durbin-Watson stat	0.038068	
Prob(F-statistic)	0.000660	Wald F-statistic	8.513353	
Prob(Wald F-statistic)	0.004497			

Regression results of model 2, using the explanatory variable of the yield spread and inflation

Dependent Variable: Y1
Method: Least Squares
Date: 05/07/15 Time: 17:17
Sample (adjusted): 1 103
Included observations: 103 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.036659	0.003828	9.577532	0.0000
X1	0.163734	0.194220	0.843035	0.4012
X2	-0.632924	0.125629	-5.038040	0.0000

R-squared 0.248371 Mean dependent var 0.019114
Adjusted R-squared 0.233339 S.D. dependent var 0.024679
S.E. of regression 0.021609 Akaike info criterion -4.802724
Sum squared resid 0.046695 Schwarz criterion -4.725985
Log likelihood 250.3403 Hannan-Quinn criter. -4.771642
F-statistic 16.52220 Durbin-Watson stat 0.849226
Prob(F-statistic) 0.000001 Wald F-statistic 13.66005
Prob(Wald F-statistic) 0.000006

Dependent Variable: Y2
Method: Least Squares
Date: 05/07/15 Time: 17:18
Sample (adjusted): 1 102
Included observations: 102 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.034898	0.004438	7.864106	0.0000
X1	0.258144	0.214975	1.200811	0.2327
X2	-0.566187	0.126191	-4.486755	0.0000

R-squared 0.279763 Mean dependent var 0.019070
Adjusted R-squared 0.265213 S.D. dependent var 0.022605
S.E. of regression 0.019377 Akaike info criterion -5.020534
Sum squared resid 0.037170 Schwarz criterion -4.943329
Log likelihood 259.0472 Hannan-Quinn criter. -4.989271
F-statistic 19.22736 Durbin-Watson stat 0.437086
Prob(F-statistic) 0.000000 Wald F-statistic 13.43775
Prob(Wald F-statistic) 0.000007

Dependent Variable: Y3
Method: Least Squares
Date: 05/07/15 Time: 17:20
Sample (adjusted): 1 101
Included observations: 101 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.033134	0.005282	6.272952	0.0000
X1	0.331089	0.244565	1.353791	0.1789
X2	-0.497494	0.138030	-3.604243	0.0005

R-squared 0.291894 Mean dependent var 0.019088
Adjusted R-squared 0.277443 S.D. dependent var 0.021246
S.E. of regression 0.018060 Akaike info criterion -5.160960
Sum squared resid 0.031965 Schwarz criterion -5.083283
Log likelihood 263.6285 Hannan-Quinn criter. -5.129514
F-statistic 20.19870 Durbin-Watson stat 0.322772
Prob(F-statistic) 0.000000 Wald F-statistic 14.38106
Prob(Wald F-statistic) 0.000003

Dependent Variable: Y4
Method: Least Squares
Date: 05/07/15 Time: 17:20
Sample (adjusted): 1 100
Included observations: 100 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.031374	0.006069	5.169430	0.0000
X1	0.388529	0.271632	1.430349	0.1558
X2	-0.428981	0.158877	-2.700082	0.0082

R-squared 0.299168 Mean dependent var 0.019115
Adjusted R-squared 0.284718 S.D. dependent var 0.019973
S.E. of regression 0.016892 Akaike info criterion -5.294404
Sum squared resid 0.027678 Schwarz criterion -5.216249
Log likelihood 267.7202 Hannan-Quinn criter. -5.262773
F-statistic 20.70348 Durbin-Watson stat 0.231741
Prob(F-statistic) 0.000000 Wald F-statistic 15.09548
Prob(Wald F-statistic) 0.000002

Dependent Variable: Y5
Method: Least Squares
Date: 05/07/15 Time: 17:21
Sample (adjusted): 1 99
Included observations: 99 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.029838	0.006187	4.822896	0.0000
X1	0.429441	0.266970	1.608572	0.1110
X2	-0.370895	0.166110	-2.232830	0.0279

R-squared 0.304952 Mean dependent var 0.019104
Adjusted R-squared 0.290472 S.D. dependent var 0.018908
S.E. of regression 0.015927 Akaike info criterion -5.411820
Sum squared resid 0.024351 Schwarz criterion -5.333180
Log likelihood 270.8851 Hannan-Quinn criter. -5.380002
F-statistic 21.05999 Durbin-Watson stat 0.189985
Prob(F-statistic) 0.000000 Wald F-statistic 16.53050
Prob(Wald F-statistic) 0.000001

Dependent Variable: Y6
Method: Least Squares
Date: 05/07/15 Time: 17:21
Sample (adjusted): 1 98
Included observations: 98 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.028755	0.006160	4.667896	0.0000
X1	0.435687	0.257050	1.694952	0.0934
X2	-0.330466	0.168614	-1.959896	0.0529

R-squared 0.305195 Mean dependent var 0.019101
Adjusted R-squared 0.290568 S.D. dependent var 0.017940
S.E. of regression 0.015110 Akaike info criterion -5.516733
Sum squared resid 0.021691 Schwarz criterion -5.437601
Log likelihood 273.3199 Hannan-Quinn criter. -5.484725
F-statistic 20.86452 Durbin-Watson stat 0.146699
Prob(F-statistic) 0.000000 Wald F-statistic 16.41554
Prob(Wald F-statistic) 0.000001

Dependent Variable: Y7
Method: Least Squares
Date: 05/07/15 Time: 17:21
Sample (adjusted): 1 97
Included observations: 97 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.028025	0.005923	4.731756	0.0000
X1	0.403589	0.240716	1.676617	0.0969
X2	-0.301874	0.164639	-1.833549	0.0699

R-squared	0.288413	Mean dependent var	0.019178
Adjusted R-squared	0.273273	S.D. dependent var	0.017054
S.E. of regression	0.014538	Akaike info criterion	-5.593612
Sum squared resid	0.019868	Schwarz criterion	-5.513981
Log likelihood	274.2902	Hannan-Quinn criter.	-5.561413
F-statistic	19.04953	Durbin-Watson stat	0.117970
Prob(F-statistic)	0.000000	Wald F-statistic	14.31593
Prob(Wald F-statistic)	0.000004		

Dependent Variable: Y16
Method: Least Squares
Date: 05/07/15 Time: 17:22
Sample (adjusted): 1 88
Included observations: 88 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.021985	0.004674	4.703488	0.0000
X1	0.299412	0.167815	1.784176	0.0780
X2	-0.042114	0.128140	-0.328657	0.7432

R-squared	0.129665	Mean dependent var	0.020462
Adjusted R-squared	0.109186	S.D. dependent var	0.012287
S.E. of regression	0.011596	Akaike info criterion	-6.042744
Sum squared resid	0.011431	Schwarz criterion	-5.958290
Log likelihood	268.8807	Hannan-Quinn criter.	-6.008720
F-statistic	6.331768	Durbin-Watson stat	0.037063
Prob(F-statistic)	0.002733	Wald F-statistic	4.857685
Prob(Wald F-statistic)	0.010056		

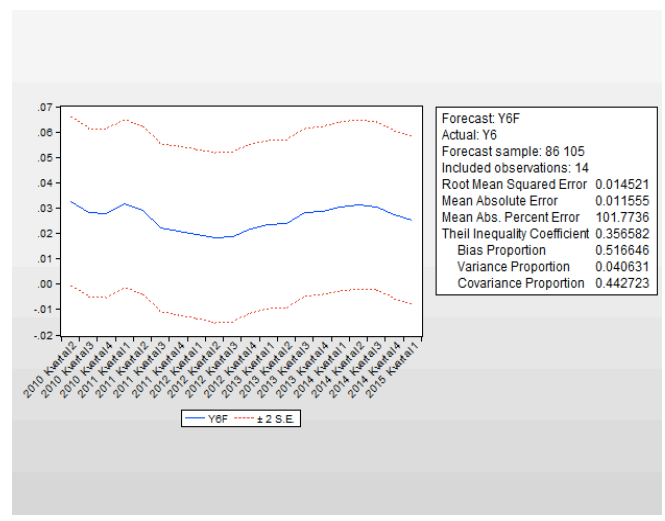
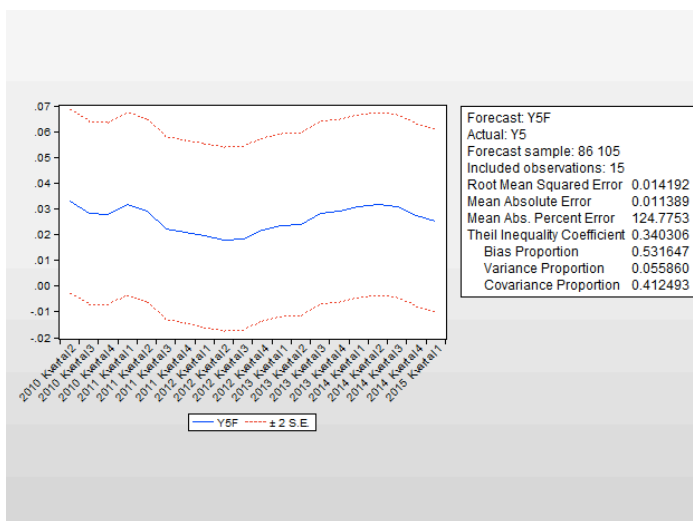
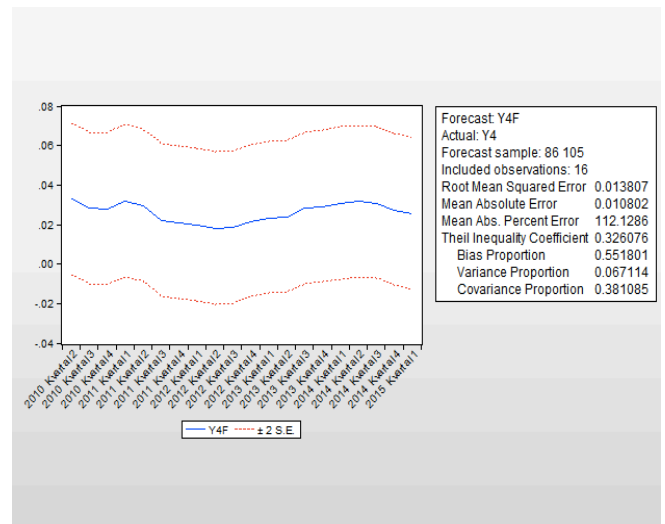
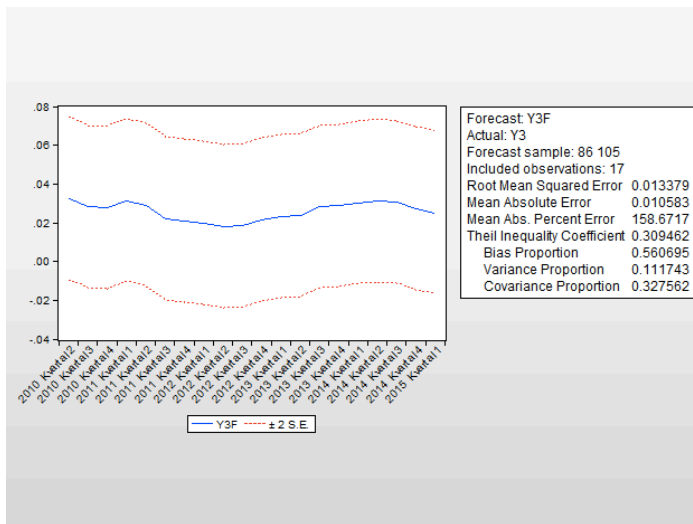
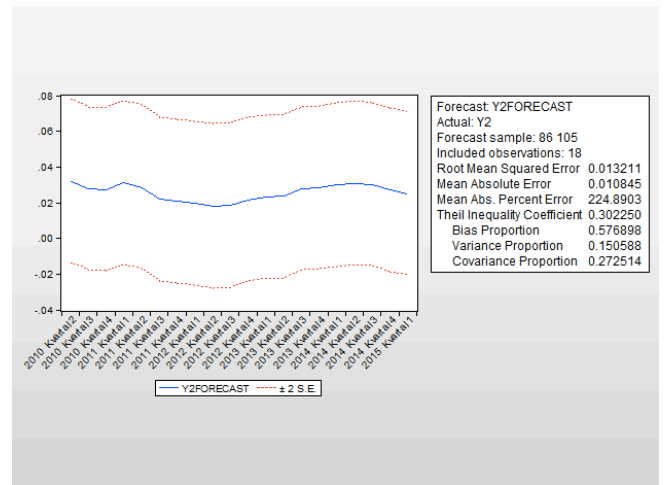
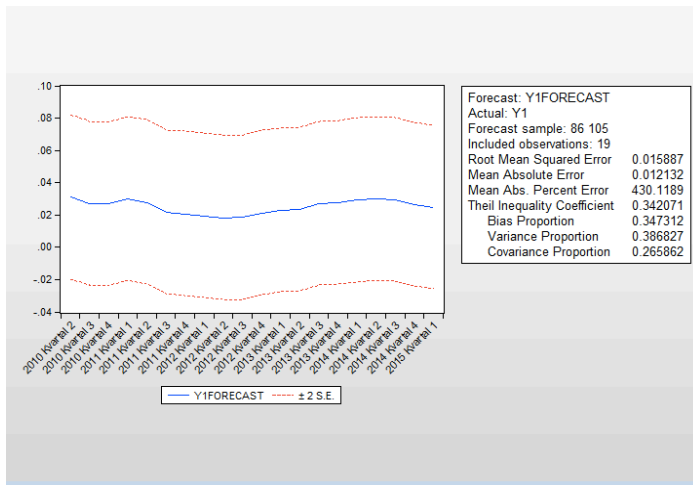
Dependent Variable: Y8
Method: Least Squares
Date: 05/07/15 Time: 17:21
Sample (adjusted): 1 96
Included observations: 96 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000)

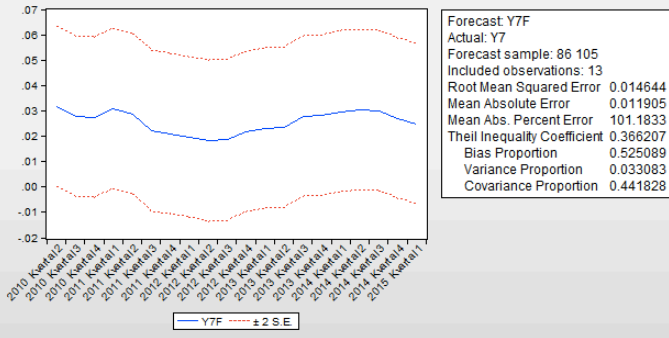
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.027301	0.005641	4.839529	0.0000
X1	0.365612	0.224641	1.627540	0.1070
X2	-0.273277	0.159644	-1.711796	0.0903

R-squared	0.262557	Mean dependent var	0.019275
Adjusted R-squared	0.246698	S.D. dependent var	0.016268
S.E. of regression	0.014120	Akaike info criterion	-5.651744
Sum squared resid	0.018541	Schwarz criterion	-5.571609
Log likelihood	274.2837	Hannan-Quinn criter.	-5.619352
F-statistic	16.55571	Durbin-Watson stat	0.105450
Prob(F-statistic)	0.000001	Wald F-statistic	11.45361
Prob(Wald F-statistic)	0.000036		

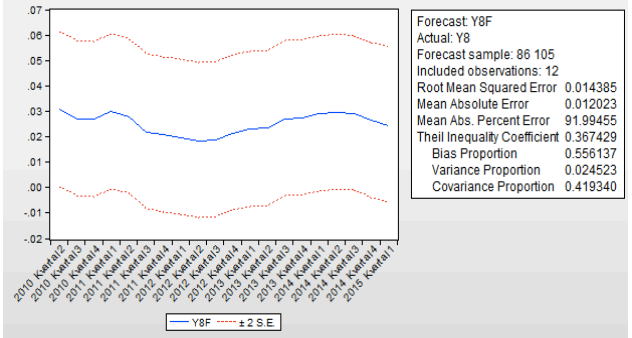
8.3 Forecast Results

Forecasting results of model 1 for sample period 2009:3 to 2014:3

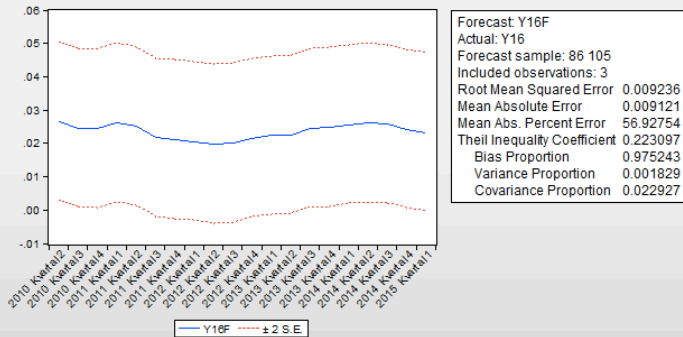




Forecast: Y7F
 Actual: Y7
 Forecast sample: 86 105
 Included observations: 13
 Root Mean Squared Error 0.014644
 Mean Absolute Error 0.011905
 Mean Abs. Percent Error 101.1833
 Theil Inequality Coefficient 0.366207
 Bias Proportion 0.525089
 Variance Proportion 0.033083
 Covariance Proportion 0.441828

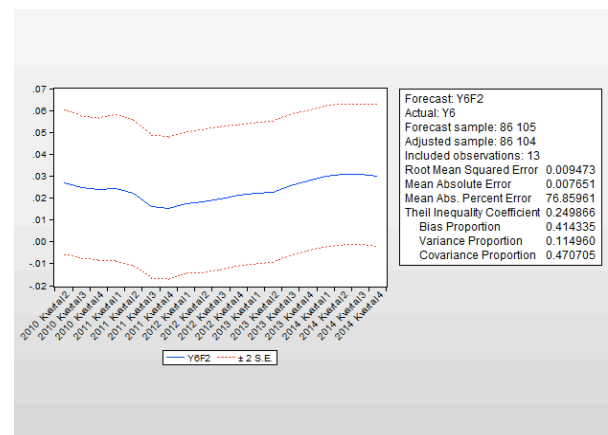
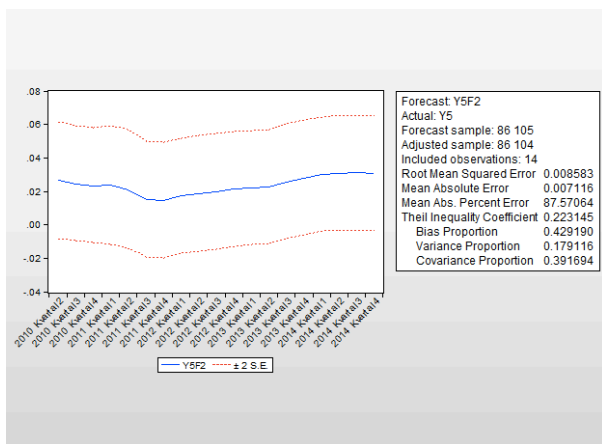
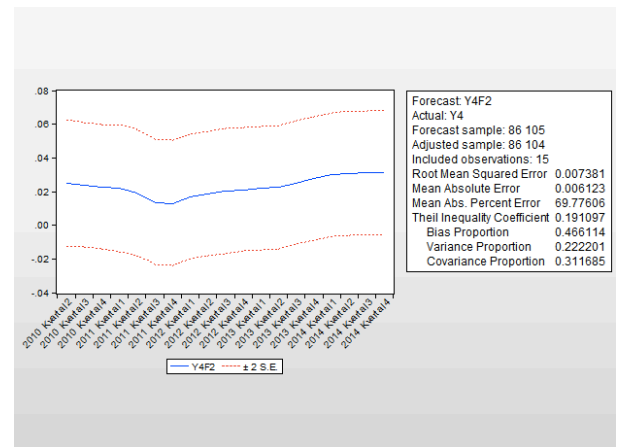
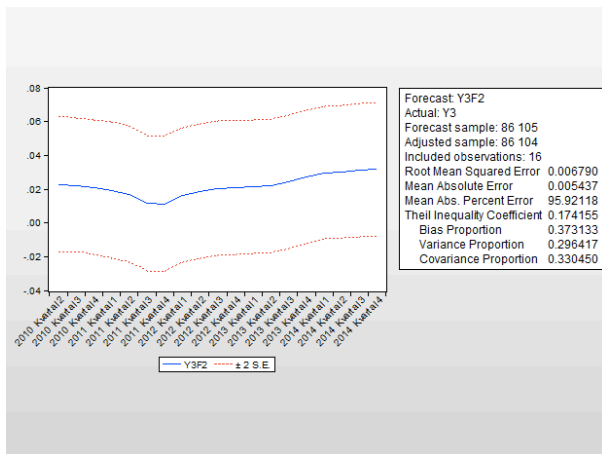
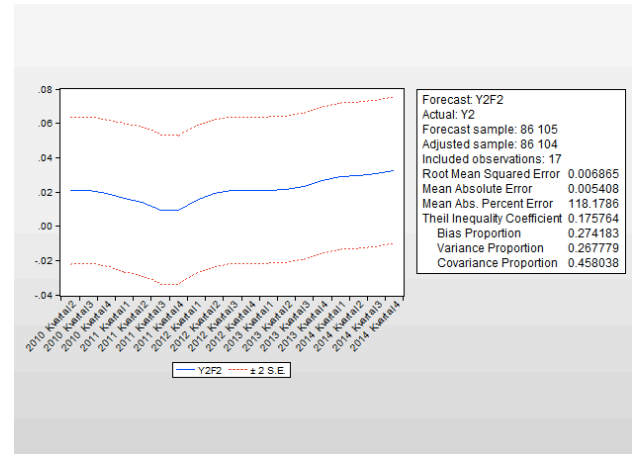
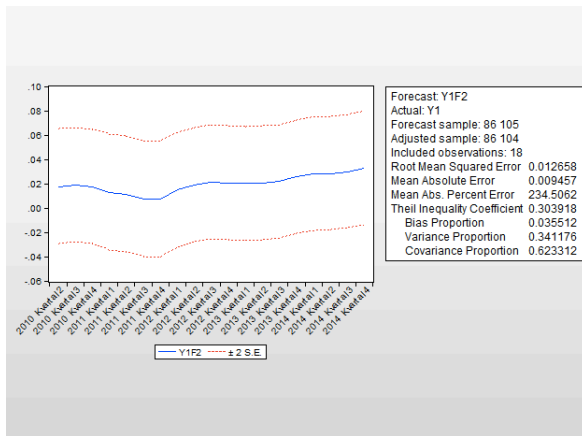


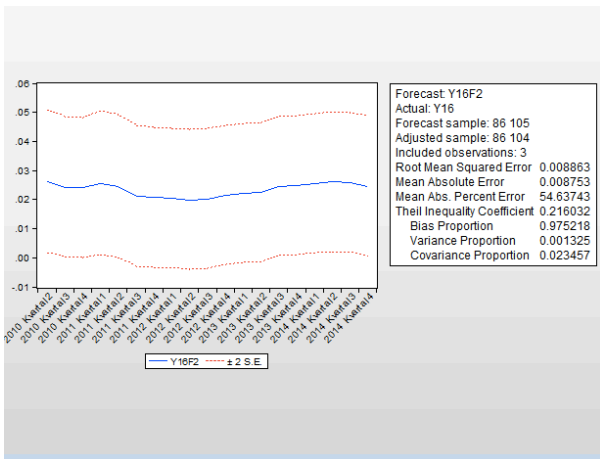
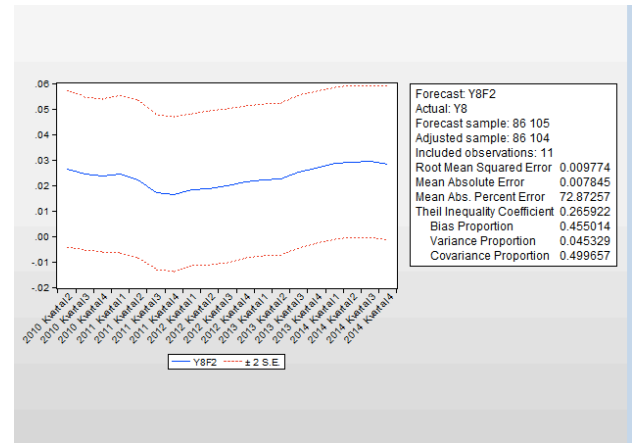
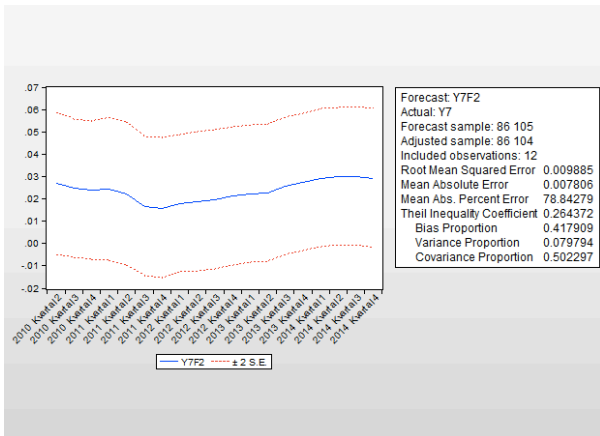
Forecast: Y8F
 Actual: Y8
 Forecast sample: 86 105
 Included observations: 12
 Root Mean Squared Error 0.014385
 Mean Absolute Error 0.012023
 Mean Abs. Percent Error 91.99455
 Theil Inequality Coefficient 0.367429
 Bias Proportion 0.556137
 Variance Proportion 0.024523
 Covariance Proportion 0.419340



Forecast: Y16F
 Actual: Y16
 Forecast sample: 86 105
 Included observations: 3
 Root Mean Squared Error 0.009236
 Mean Absolute Error 0.009121
 Mean Abs. Percent Error 56.92754
 Theil Inequality Coefficient 0.223097
 Bias Proportion 0.975243
 Variance Proportion 0.001829
 Covariance Proportion 0.022927

Forecasting results of model 2 for sample period 2009:3 to 2014:3





8.4 Forecast Regressions

Forecast regression results for model 1, sample period 2009:3 to 2014:3

Dependent Variable: Y1 Method: Least Squares Date: 05/14/15 Time: 17:04 Sample: 86 105 Included observations: 19				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.019610	0.019199	-1.021375	0.3214
Y1FORECAST	1.408507	0.755447	1.864467	0.0796
R-squared	0.169769	Mean dependent var	0.015721	
Adjusted R-squared	0.120932	S.D. dependent var	0.014349	
S.E. of regression	0.013454	Akaike info criterion	-5.679807	
Sum squared resid	0.003077	Schwarz criterion	-5.580393	
Log likelihood	55.95817	Hannan-Quinn criter.	-5.662982	
F-statistic	3.476238	Durbin-Watson stat	2.613692	
Prob(F-statistic)	0.079617			

Dependent Variable: Y2 Method: Least Squares Date: 05/14/15 Time: 17:14 Sample: 86 105 Included observations: 18				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.008650	0.012456	-0.694444	0.4974
Y2FORECAST	0.945305	0.484818	1.949816	0.0689
R-squared	0.191992	Mean dependent var	0.015274	
Adjusted R-squared	0.141491	S.D. dependent var	0.009833	
S.E. of regression	0.009111	Akaike info criterion	-6.454223	
Sum squared resid	0.001328	Schwarz criterion	-6.355293	
Log likelihood	60.08801	Hannan-Quinn criter.	-6.440582	
F-statistic	3.801781	Durbin-Watson stat	0.613954	
Prob(F-statistic)	0.068946			

Dependent Variable: Y3 Method: Least Squares Date: 05/14/15 Time: 16:56 Sample: 86 105 Included observations: 17				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.001214	0.012628	0.096105	0.9247
Y3F	0.554164	0.493393	1.123169	0.2790
R-squared	0.077576	Mean dependent var	0.015174	
Adjusted R-squared	0.016081	S.D. dependent var	0.009268	
S.E. of regression	0.009193	Akaike info criterion	-6.430568	
Sum squared resid	0.001268	Schwarz criterion	-6.332543	
Log likelihood	56.65983	Hannan-Quinn criter.	-6.420824	
F-statistic	1.261509	Durbin-Watson stat	0.602184	
Prob(F-statistic)	0.279021			

Dependent Variable: Y4 Method: Least Squares Date: 05/14/15 Time: 16:58 Sample: 86 105 Included observations: 16				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.013761	0.012131	1.134308	0.2757
Y4F	0.041104	0.476499	0.086263	0.9325
R-squared	0.000531	Mean dependent var	0.014790	
Adjusted R-squared	-0.070859	S.D. dependent var	0.008410	
S.E. of regression	0.008703	Akaike info criterion	-6.533872	
Sum squared resid	0.001060	Schwarz criterion	-6.437298	
Log likelihood	54.27097	Hannan-Quinn criter.	-6.528926	
F-statistic	0.007441	Durbin-Watson stat	0.208901	
Prob(F-statistic)	0.932479			

Dependent Variable: Y5 Method: Least Squares Date: 05/14/15 Time: 16:59 Sample: 86 105 Included observations: 15				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.020160	0.011979	1.683003	0.1162
Y5F	-0.230684	0.475090	-0.485559	0.6354
R-squared	0.017813	Mean dependent var	0.014442	
Adjusted R-squared	-0.057740	S.D. dependent var	0.008238	
S.E. of regression	0.008473	Akaike info criterion	-6.580350	
Sum squared resid	0.000933	Schwarz criterion	-6.485943	
Log likelihood	51.35263	Hannan-Quinn criter.	-6.581356	
F-statistic	0.235767	Durbin-Watson stat	0.409301	
Prob(F-statistic)	0.635361			

Dependent Variable: Y6 Method: Least Squares Date: 05/14/15 Time: 16:59 Sample: 86 105 Included observations: 14				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.028912	0.010946	2.641418	0.0215
Y6F	-0.610436	0.440391	-1.386121	0.1909
R-squared	0.138014	Mean dependent var	0.013997	
Adjusted R-squared	0.066181	S.D. dependent var	0.007761	
S.E. of regression	0.007499	Akaike info criterion	-6.816444	
Sum squared resid	0.000675	Schwarz criterion	-6.725150	
Log likelihood	49.71511	Hannan-Quinn criter.	-6.824895	
F-statistic	1.921332	Durbin-Watson stat	0.376334	
Prob(F-statistic)	0.190927			

Dependent Variable: Y7				
Method: Least Squares				
Date: 05/14/15 Time: 17:00				
Sample: 86 105				
Included observations: 13				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.034099	0.010145	3.361040	0.0064
Y7F	-0.844400	0.411802	-2.050498	0.0649
R-squared	0.276532	Mean dependent var		0.013630
Adjusted R-squared	0.210762	S.D. dependent var		0.007349
S.E. of regression	0.006529	Akaike info criterion		-7.084603
Sum squared resid	0.000469	Schwarz criterion		-6.997688
Log likelihood	48.04992	Hannan-Quinn criter.		-7.102468
F-statistic	4.204543	Durbin-Watson stat		0.497304
Prob(F-statistic)	0.064920			

Dependent Variable: Y8				
Method: Least Squares				
Date: 05/14/15 Time: 17:05				
Sample: 86 105				
Included observations: 12				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.036373	0.009291	3.914834	0.0029
Y8F	-0.960433	0.381036	-2.520585	0.0304
R-squared	0.388504	Mean dependent var		0.013298
Adjusted R-squared	0.327355	S.D. dependent var		0.006703
S.E. of regression	0.005497	Akaike info criterion		-7.418170
Sum squared resid	0.000302	Schwarz criterion		-7.337352
Log likelihood	46.50902	Hannan-Quinn criter.		-7.448092
F-statistic	6.353349	Durbin-Watson stat		0.430755
Prob(F-statistic)	0.030357			

Dependent Variable: Y16				
Method: Least Squares				
Date: 05/14/15 Time: 17:06				
Sample (adjusted): 86 88				
Included observations: 3 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.024820	0.012711	1.952682	0.3013
Y16F	-0.344528	0.503116	-0.684788	0.6177
R-squared	0.319234	Mean dependent var		0.016123
Adjusted R-squared	-0.361531	S.D. dependent var		0.000756
S.E. of regression	0.000882	Akaike info criterion		-10.99380
Sum squared resid	7.78E-07	Schwarz criterion		-11.59473
Log likelihood	18.49070	Hannan-Quinn criter.		-12.20174
F-statistic	0.468934	Durbin-Watson stat		2.604891
Prob(F-statistic)	0.617746			

Forecast regression results for model 1, sample period 2009:3 to 2014:3

Dependent Variable: Y1 Method: Least Squares Date: 05/14/15 Time: 17:06 Sample (adjusted): 86 103 Included observations: 18 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.001330	0.009666	-0.137624	0.8923
Y1F2	0.944411	0.482240	1.958383	0.0679
R-squared	0.193356	Mean dependent var	0.016595	
Adjusted R-squared	0.142941	S.D. dependent var	0.014236	
S.E. of regression	0.013180	Akaike info criterion	-5.715855	
Sum squared resid	0.002779	Schwarz criterion	-5.616925	
Log likelihood	53.44270	Hannan-Quinn criter.	-5.702214	
F-statistic	3.835263	Durbin-Watson stat	2.875375	
Prob(F-statistic)	0.067855			

Dependent Variable: Y2 Method: Least Squares Date: 05/14/15 Time: 17:07 Sample (adjusted): 86 102 Included observations: 17 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.009312	0.005410	-1.721361	0.1057
Y2F2	1.289238	0.263623	4.890463	0.0002
R-squared	0.614561	Mean dependent var	0.016172	
Adjusted R-squared	0.588865	S.D. dependent var	0.009343	
S.E. of regression	0.005991	Akaike info criterion	-7.287016	
Sum squared resid	0.000538	Schwarz criterion	-7.188991	
Log likelihood	63.93963	Hannan-Quinn criter.	-7.277272	
F-statistic	23.91663	Durbin-Watson stat	1.468220	
Prob(F-statistic)	0.000196			

Dependent Variable: Y3 Method: Least Squares Date: 05/14/15 Time: 17:07 Sample (adjusted): 86 101 Included observations: 16 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.013099	0.005860	-2.235281	0.0422
Y3F2	1.441588	0.281608	5.119124	0.0002
R-squared	0.651788	Mean dependent var	0.016123	
Adjusted R-squared	0.626916	S.D. dependent var	0.008678	
S.E. of regression	0.005301	Akaike info criterion	-7.525458	
Sum squared resid	0.000393	Schwarz criterion	-7.428885	
Log likelihood	62.20367	Hannan-Quinn criter.	-7.520513	
F-statistic	26.20543	Durbin-Watson stat	1.951080	
Prob(F-statistic)	0.000156			

Dependent Variable: Y4 Method: Least Squares Date: 05/14/15 Time: 17:08 Sample (adjusted): 86 100 Included observations: 15 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.012046	0.007778	-1.548636	0.1455
Y4F2	1.336599	0.367128	3.640688	0.0030
R-squared	0.504849	Mean dependent var	0.015776	
Adjusted R-squared	0.466760	S.D. dependent var	0.007688	
S.E. of regression	0.005614	Akaike info criterion	-7.403406	
Sum squared resid	0.000410	Schwarz criterion	-7.308999	
Log likelihood	57.52554	Hannan-Quinn criter.	-7.404412	
F-statistic	13.25461	Durbin-Watson stat	0.518496	
Prob(F-statistic)	0.002990			

Dependent Variable: Y5 Method: Least Squares Date: 05/14/15 Time: 17:08 Sample (adjusted): 86 99 Included observations: 14 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.003221	0.011191	-0.287856	0.7784
Y5F2	0.886158	0.523037	1.694255	0.1160
R-squared	0.193033	Mean dependent var	0.015473	
Adjusted R-squared	0.125786	S.D. dependent var	0.007477	
S.E. of regression	0.006991	Akaike info criterion	-6.956924	
Sum squared resid	0.000586	Schwarz criterion	-6.865630	
Log likelihood	50.69847	Hannan-Quinn criter.	-6.965375	
F-statistic	2.870499	Durbin-Watson stat	0.445384	
Prob(F-statistic)	0.115989			

Dependent Variable: Y6 Method: Least Squares Date: 05/14/15 Time: 17:08 Sample (adjusted): 86 98 Included observations: 13 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.012234	0.012507	0.978173	0.3490
Y6F2	0.134090	0.583210	0.229917	0.8224
R-squared	0.004783	Mean dependent var	0.015073	
Adjusted R-squared	-0.085692	S.D. dependent var	0.006904	
S.E. of regression	0.007194	Akaike info criterion	-6.890620	
Sum squared resid	0.000569	Schwarz criterion	-6.803704	
Log likelihood	46.78903	Hannan-Quinn criter.	-6.908485	
F-statistic	0.052862	Durbin-Watson stat	0.230684	
Prob(F-statistic)	0.822376			

Dependent Variable: Y7				
Method: Least Squares				
Date: 05/14/15 Time: 17:09				
Sample (adjusted): 86 97				
Included observations: 12 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.023159	0.012192	1.899478	0.0867
Y7F2	-0.396708	0.569368	-0.696751	0.5018
R-squared	0.046299	Mean dependent var	0.014766	
Adjusted R-squared	-0.049072	S.D. dependent var	0.006373	
S.E. of regression	0.006528	Akaike info criterion	-7.074496	
Sum squared resid	0.000426	Schwarz criterion	-6.993678	
Log likelihood	44.44698	Hannan-Quinn criter.	-7.104418	
F-statistic	0.485462	Durbin-Watson stat	0.393435	
Prob(F-statistic)	0.501833			

Dependent Variable: Y8				
Method: Least Squares				
Date: 05/14/15 Time: 17:09				
Sample (adjusted): 86 96				
Included observations: 11 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.030161	0.010562	2.855606	0.0189
Y8F2	-0.741871	0.495065	-1.498534	0.1682
R-squared	0.199687	Mean dependent var	0.014507	
Adjusted R-squared	0.110764	S.D. dependent var	0.005489	
S.E. of regression	0.005176	Akaike info criterion	-7.526683	
Sum squared resid	0.000241	Schwarz criterion	-7.454338	
Log likelihood	43.39676	Hannan-Quinn criter.	-7.572286	
F-statistic	2.245605	Durbin-Watson stat	0.407481	
Prob(F-statistic)	0.168224			

Dependent Variable: Y16				
Method: Least Squares				
Date: 05/14/15 Time: 17:09				
Sample (adjusted): 86 88				
Included observations: 3 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.025733	0.013221	1.946364	0.3021
Y16F2	-0.386336	0.531111	-0.727412	0.5996
R-squared	0.346033	Mean dependent var	0.016123	
Adjusted R-squared	-0.307934	S.D. dependent var	0.000756	
S.E. of regression	0.000865	Akaike info criterion	-11.03396	
Sum squared resid	7.47E-07	Schwarz criterion	-11.63489	
Log likelihood	18.55094	Hannan-Quinn criter.	-12.24190	
F-statistic	0.529129	Durbin-Watson stat	2.649188	
Prob(F-statistic)	0.599638			