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PREDICTING EUROPEAN UNION RECESSIONS IN THE EURO ERA: THE YIELD CURVE AS A FORECASTING TOOL OF ECONOMIC ACTIVITY

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ABSTRACT

Several studies have established the predictive power of the yield curve, ie: the difference between long and short term bond rates, in terms of real economic activity, for the U.S. and various European countries. In this paper we use data from the European Union (EU15), ranging from 1994:Q1 to 2008:Q3. The seasonally adjusted real GDP is used to extract the long run trend and the cyclical component of the European output, while the European Central Bank's euro area government benchmark bonds of various maturities are used for the calculation of the yield spreads. We also augment the models tested with non monetary policy variables: the unemployment and a composite European stock price index constructed from the indices of the three major European stock markets of London, Frankfurt and Paris. The methodology employed in the effort to forecast recessions, is a probit model of the inverse cumulative distribution function of the standard distribution, using several formal forecasting evaluation tests. The results show that the yield curve augmented with the composite stock index has significant forecasting power in terms of the EU15 real output.

Keywords: forecasting, yield spread, recession, probit, term structure, monetary policy, real growth.

JEL classification: E43, E44, E52, C53

1. Introduction

The yield curve, measuring the difference between short and long term interest rates is at the center of recession forecasting. This is the case because a short term interest rate is an instrument of the monetary policy. Thus, it may contain useful information to policy makers and other individuals. Most of the empirical research gives rise to this theoretical standpoint, by examining the economies of industrialized countries. There are two major categories of empirical tests. According to the first, using OLS estimators researchers try to predict future economic activity, and in the second category, probit models are used to forecast upcoming recessions. According to Estrella and Mishkin (1997), the short end of the yield curve can be affected by the European Central Bank or the Federal Reserve or any other central bank, but the long end will be determined by many other considerations, including long term expectations of inflation and real economic activity. In their influential paper, after taking into account monetary policy conducted in four major European countries (France, Germany, Italy and U.K), they show that the term structure spread has significant predictive power for both real activity and inflation. Bonser and Morley (1997) after examining eleven developed economies found that the yield spread is a good predictive instrument for future economic activity. In the same vein, Venetis et al (2003) reached the same conclusions as well as Hamilton and Kim (2002). On the other hand, Kim and Limpaphayon (1991) testing Japan, found evidence that the expected short term interest rate is the only source of predictability for Japan and not the term premium. Andrew Ang et al (2005) after modeling regressor endogeneity and using data for the period 1952 to 2001, conclude that the short term interest rate has more predictive power than any term spread. They confirm their finding by forecasting GDP out of sample. There is also, a class of papers that use probit models to forecast recessions. Wright (2006) using as explanatory variables the federal reserve funds rate and the term spread forecasts recessions 6 quarters ahead for the U.S economy. Chauvet and Potter (2005), propose out of sample forecasting performance using standard probabilities as well as “hitting probabilities” of recession that take into account the length of business cycle phases. They found, that standard probit specification tends to over predict recession results.

2. The Data

We measure economic activity within the European Union in terms of the EU15 GDP which is comprised of the fifteen countries that participated in the Union before the enlargement of May 1, 2004. The data for the group EU15 are quarterly GDP data from the OECD data base. They are seasonally adjusted for the period 1994:Q1 to 2008:Q3. Before taking the natural logarithm of the GDP series we apply the OECD seasonally adjusted GDP deflator with base year the year 2000 and we get the seasonally adjusted EU15 real GDP. The aim of the paper is to predict deviations of real output from the long term trend and especially the probability that the GDP of a particular quarter will be below the long run trend. For this reason, we first decompose the EU15 seasonally adjusted real GDP to the trend and cyclical component employing the Hodrick-Prescott (1997) filter (HP)[1]. The HP filter is commonly used in the area of real business cycles[2]. It produces a smooth non-linear trend which is affected more from the long-term fluctuations rather than the short-term ones. The adaptation of the filter sensitivity in long-term fluctuations is achieved through the use of the factor λ which takes certain numbers depending on the data frequency. The filter's contribution is to distinguish an observed shock into a component that causes permanent effects and a component that has provisional effects on the economy. Through the use of the HP filter the main object is the extraction of the trend, τ_t, from a time series y_t so as to isolate the cyclical component c_t via the process of minimising the fluctuations of variable y_t around its long lasting trend τ_t. The minimisation of τ_t is calculated as follows:

$$\min_{\tau_t} \sum_{t=1}^{T}(y_t-\tau_t)^2+\lambda\sum_{t=2}^{T-1}[(\tau_{t+1}-\tau_t)-(\tau_t-\tau_{t-1})]^2$$

where y_t is the initial time series and τ_t is the long-term trend and t = 1, 2, …, T. The term $\sum_{t=1}^{T}(y_t-\tau_t)^2$ measures the adaptation (fitness) of the time series while the term $\lambda\sum_{t=2}^{T-1}[(\tau_{t+1}-\tau_t)-(\tau_t-\tau_{t-1})]^2$ measures the degree of smoothness of the trend. The minimisation of equation (1) contributes to the extraction of the trend τ_t from the time

[1] Hodrick, R., and E.P. Prescott (1997), "Postwar Business Cycles: An Empirical Investigation," Journal of Money, Credit, and Banking.

[2] Cogley, T. and J.M. Nason., (1995), Effects of the Hodrick-Prescott Filter on Trend and Difference Stationary Time Series: Implications for Business Cycle Research, Journal of Economic Dynamics and Control, p. 254.

series y_t with the cyclical component c_t being determined from the time series residuals. The factor λ measures the degree of smoothness of the calculated trend. When $\lambda = 0$ the trend component is equal to the variable y_t. As λ increases, the trend component becomes increasingly linear. For quarterly data, Hodrick and Prescott (1997) proposed the use of $\lambda = 1600$. Having extracted the cyclical component of the EU15 real GDP we then construct the business cycle dummy variable BS that takes the value one whenever the cycle is negative implying that the GDP is below trend, and the value zero elsewhere. In Figures 1 and 2 we graph the seasonally adjusted quarterly real GDP in logarithms along with the extracted trend and also the cyclical component. It is important to be noted here that for the purposes of this paper we define recessions as the negative deviations of GDP from the long term trend. In other words, our aim is to use the yield spread information and other explanatory variables in order to forecast negative values for the cyclical component of the quarterly EU15 seasonally adjusted real GDP as it is extracted employing the Hodrick-Prescott (1997) filter.

The explanatory variables we use are the yield spreads, the EU15 unemployment rate and the stock indices of the London, Frankfurt, and Paris stock exchanges. All interest rates used in calculating the yield spreads are extracted from the ECB statistics and are the interest rates for the euro area government benchmark bonds with maturities for the long term rates one, two, five and ten years, and for the short term rates with maturities one and three months - see Figures 3 and 4. The EU15 unemployment rate is obtained from the Eurostat database and graphed in Figure 5. Finally, the stock index is a composite index of the three major European stock exchanges, namely, London, Frankfurt and Paris using the FTSE-100, DAX and CAC-40, indices respectively as it is depicted in Figure 6. The stock data are obtained from Six Telekurs. In Table 1 we present a statistical summary of the explanatory variables.

3. Methodology and Empirical Results

We consider forty eight alternative models for probit regressions forecasting a quarterly GDP cycle below trend at some point within the next h quarters:

$$prob(BS_t = 1) = \Phi[\tilde{a}_0 + \tilde{a}_1 (i_{LR,t-i} - i_{SR,t-i})], \qquad (1)$$

where BS_t is the dummy variable that takes the value one every time the cyclical component of the GDP is negative implying a below trend GDP, and zero elsewhere. $\Phi(.)$ denotes the standard normal cumulative distribution function, $(i_{LR,t-i} - i_{SR,t-i})$ represents the spread between the long and short run interest rates with $i = 1,...,6$. For the long run interest rates we use four rates alternatively, the one, two, five and ten year rates, while for the short run rates we use two alternatives, the one and three months maturities. Finally, $\tilde{a}_0$ and $\tilde{a}_1$ are the estimated parameters. Thus, equation (1) is estimated for all combinations of the short with the long run interest rates and forecast windows from one to six quarters ahead, a total of forty eight probit regressions. The estimated coefficient of the spread $\tilde{a}_1$, is statistically significant at probabilities $p < .01$ only for the one year/one month, two years/one month, one year/three months and two years/three months spreads and at forecast window $i = 2$ quarters and for the one year/one month spread at forecast window $i = 3$ quarters. As the main purpose of this paper is the prediction of GDP economic activity below the long run trend, we formally compare the above five models in terms of their forecasting ability by calculating the root mean squared error (RMSE), mean absolute error (MAE), and the mean absolute percent error (MAPE) statistics. These statistics are calculated using the following formulas:

$$RMSE = \sqrt{\frac{1}{F}\sum_{f=1}^{F} e_{t+f}^2}$$

$$MAE = \frac{1}{F}\sum_{f=1}^{F} \left| e_{t+f} \right|$$

$$MAPE = \frac{1}{F}\sum_{f=1}^{F} \left| \frac{e_{t+f,t}}{y_{t+f}} \right|$$

where $e_{t+f} = y_{t+f} - y^*_{t+f}$, and y_{t+f} is the actual value of the series at period $t+f$, y^*_{t+f} is the forecast for y_{t+f} and F is the forecast window. These statistics are summarized in Table 2. We see that model 4, the one constructed with the spread of the one year interest rate minus the three month interest rate and at forecast window two quarters, outperforms in terms of forecasting efficiency all four other models and for all three forecasting criteria. Thus, for the rest of the paper we employ this model for the purposes of prediction of the probability that the real GDP will be bellow trend. Next, in an effort to examine whether other variables from the real economy can add any informational content to the forecasts of the GDP we estimate the following probit regressions:

$$prob(BS_t = 1) = \Phi[\tilde{a}_0 + \tilde{a}_1 (i_{LR,t-i} - i_{SR,t-i}) + \tilde{a}_u u_{t-i}] \qquad (2)$$

$$prob(BS_t = 1) = \Phi[\tilde{a}_0 + \tilde{a}_1 (i_{LR,t-i} - i_{SR,t-i}) + \tilde{a}_s s_{t-i}], \qquad (3)$$

where u_t is the unemployment rate in the EU15 area, s_t is the stock market composite index and $\tilde{a}_u$, $\tilde{a}_s$ are their estimated coefficients. As we can see in Table 3, the unemployment as an explanatory variable is not statistically significant from zero in all estimated forecast windows from u_{t-1} to u_{t-6} and either probability 0.10 or 0.05. From Table 4 we see that the inclusion of the stock index as an explanatory variable is statistically significant at all forecast windows for probability 0.10 and all but three and four forecast windows at the 5% probability. Thus, we then compare the forecasting power of the previously selected model 4, the one constructed with the spread of the one year interest rate minus the three month interest rate and at forecast window two quarters and the same spread and lag structure with the inclusion of the stock index variable. The forecasting error statistics of the two compared models are presented in Table 5. According to all three statistics the model with the stock index variable is selected according to forecasting accuracy. In Figure 7, we present the forecasted probability of a recession using the best fit model already selected along with the EU15 seasonally adjusted real GDP cyclical component. According to Figure 7, the predictive power of the estimated model in terms of the forecasted probabilities of EU15 GDP deviations from the trend is very high. It seems that the yield spread between the one year and the three month euro area government benchmark bonds augmented with the composite stock index and a forecast window of two quarters ahead is a very good predictor of the cyclical behaviour of GDP in terms of its deviations from the long run trend. In Table 6, we provide the Andrews and Hosmer-Lemeshow tests of goodness of fit grouped in four quantiles of risk. According to both goodness of fit evaluation criteria, our selected model provides a very good fit and the χ^2 statistics reported at the bottom of the Table for the Hosmer-Lemeshow and Andrews tests are 0.009 and .001 respectively.

4. Conclusions

In this paper we have used several probit models to examine the power of the yield spread between long term and short term maturities of euro area benchmark bonds in predicting deviations of real output from the long run trend and especially focusing on predicting recessions. Moreover, we have included in the estimation models both the unemployment and a composite index of the London, Frankfurt and Paris stock exchanges in an effort to see whether other than monetary policy variables can add any forecasting power to the yield spread. The results, after the formal evaluation of the forecasting ability of the different yield spreads and in different forecast horizons show that the best model is the one employing the spread between the one year and the three months euro area benchmark bonds with a forecast horizon equal to two quarters ahead. The inclusion of unemployment in the best yield spread model was not statistically significant at any forecast horizons. The composite stock index on the other hand was statistically significant and according to the formal forecasting evaluation tests improved the ability of the model to predict recessions in the euro area. Overall, the final model used for forecasting appears very efficient to forecast deviations of the real output from the long run trend according to both standard formal goodness of fit tests and as it appears graphically.

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Table 1

Descriptive Statistics for the Explanatory Variables

	1-month	3-month	1-year	2-year	5-year	10-year	Unemployment	Stock Index
Mean	3.95	4.02	4.16	4.14	4.67	5.30	8.97	4512.62
Median	3.96	3.95	4.11	4.08	4.40	4.81	8.76	4651.22
Maximum	7.07	7.29	7.73	7.76	8.66	9.32	10.79	6788.52
Minimum	2.06	2.05	2.15	2.21	2.66	3.26	6.97	2291.02
Std. Dev.	1.42	1.46	1.47	1.43	1.48	1.59	1.20	1370.90
Skewness	0.52	0.51	0.61	0.87	1.13	1.12	0.20	-0.06
Kurtosis	2.49	2.47	2.76	3.33	3.68	3.25	1.65	1.85
Jarque-Bera	3.26	3.25	3.75	7.76	13.63	12.54	4.84	3.30
Probability	0.20	0.20	0.15	0.02	0.00	0.00	0.09	0.19
Sum	233.21	237.45	245.72	244.54	275.72	312.52	529.33	2.66E+05
Sum Sq. Dev.	117.11	122.84	125.75	118.21	127.02	146.93	83.76	1.09E+08
Observations	59	59	59	59	59	59	59	59

Table 2

Forecasting Model Selection Criteria

	Predicting Spread			Forecasting Criteria					
Model	Long Term Rate	Short Term Rate	Forecast Window	RMSE		MAE		MAPE	
1	One Year	One Month	2 quarters	0.4549		0.4145		20.9395	
2	One Year	One Month	3 quarters	0.4686		0.4369		22.1079	
3	Two Years	One Month	2 quarters	0.4635		0.4266		21.4223	
4	One Year	Three Month	2 quarters	0.4533	*	0.4100	*	20.8120	*
5	Two Years	Three Month	2 quarters	0.4652		0.4302		21.6184	

An asterisk denotes the minimized value of the criterion.

Table 3

Probit Estimation with Unemployment as an explanatory variable

Variable	Coefficient	Std. Error	z-Statistic	Prob.
u_{t-1}	0.180	0.156	1.150	0.250
u_{t-2}	0.152	0.153	0.994	0.320
u_{t-3}	0.104	0.152	0.683	0.495
u_{t-4}	0.018	0.153	0.119	0.905
u_{t-5}	-0.046	0.156	-0.292	0.770
u_{t-6}	-0.120	0.159	-0.754	0.451

Table 4

Probit Estimation with the Stock Index as an explanatory variable

Variable	Coefficient	Std. Error	z-Statistic	Prob.	
s_{t-1}	-0.00032	0.000	-2.152	0.031	*
s_{t-2}	-0.00028	0.000	-2.000	0.046	*
s_{t-3}	-0.00025	0.000	-1.858	0.063	
s_{t-4}	-0.00022	0.000	-1.711	0.087	
s_{t-5}	-0.00027	0.000	-2.004	0.045	*
s_{t-6}	-0.00026	0.000	-1.977	0.048	*

An asterisk denotes significancy at the 5% level.

Table 5

Forecasting Model Selection Criteria

Predicting Spread				Forecasting Criteria					
Long Term Rate	Short Term Rate	Forecast Window	Stock Index	RMSE		MAE		MAPE	
One Year	Three Month	2 quarters	no	0.4533		0.4100		20.8120	
One Year	Three Month	2 quarters	yes	0.4372	*	0.3800	*	19.3203	*

An asterisk denotes the minimized value of the criterion.

Table 6

Goodness-of-Fit Evaluation for Binary Specification

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	0.05	0.25	14	11.72	0	2.28	14	2.72
2	0.26	0.50	5	9.09	10	5.91	15	4.66
3	0.50	0.70	5	5.64	9	8.36	14	0.12
4	0.72	0.93	5	2.92	10	12.08	15	1.83
		Total	29	29.3729	29	28.6271	58	9.34254

H-L Statistic	9.34	Prob. Chi-Sq(2)	0.009
Andrews Statistic	19.25	Prob. Chi-Sq(4)	0.001

Figure 1. The GDP and GDP trend series for EU15

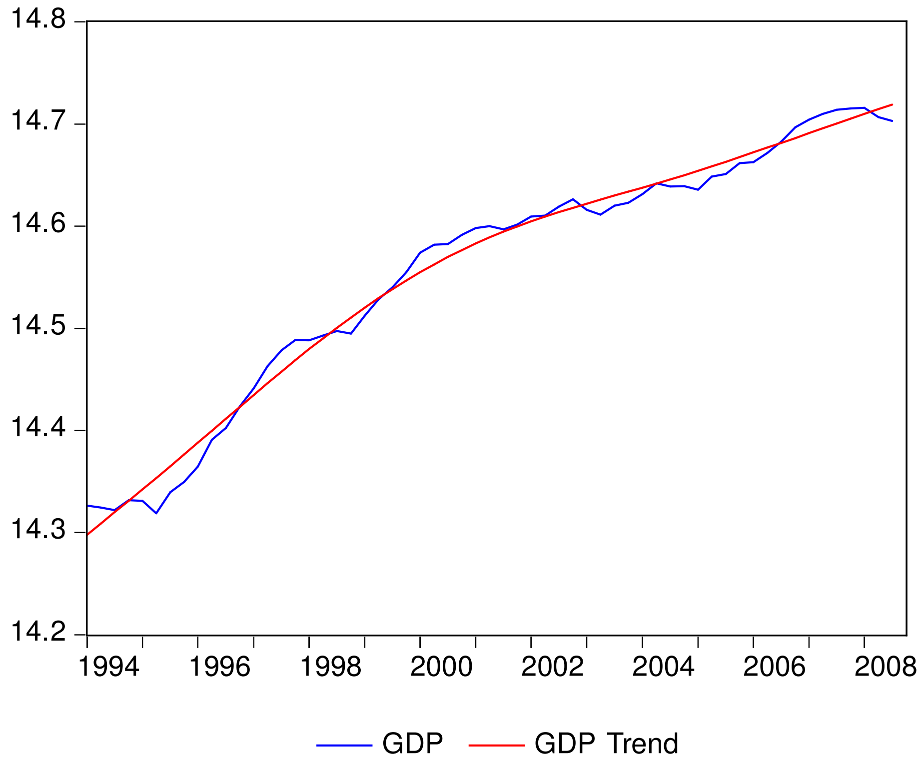

Figure 2. The extracted cyclical component of the EU15 GDP

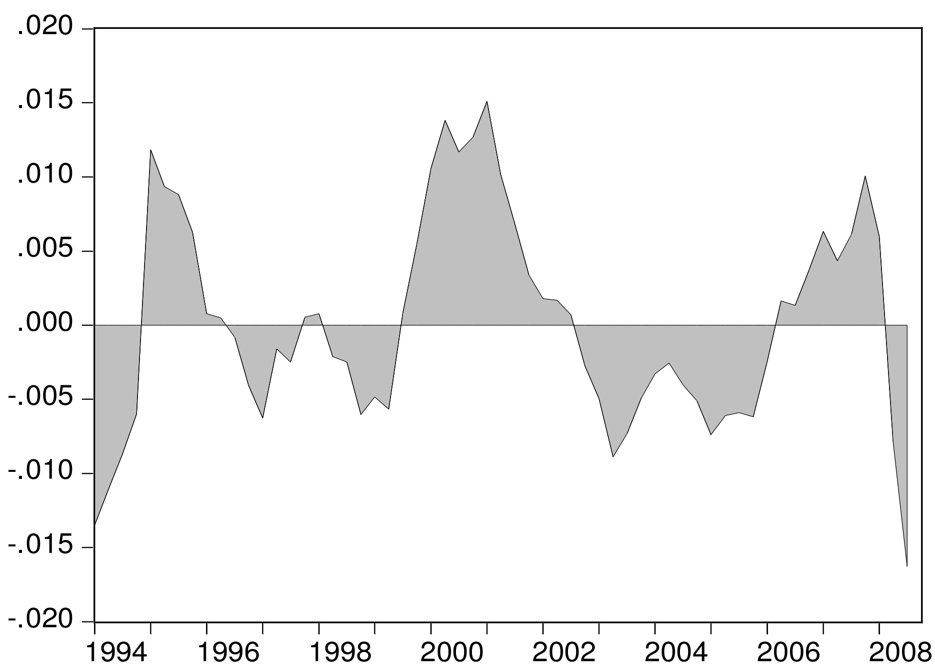

Figure 3. Short Term Interest Rates

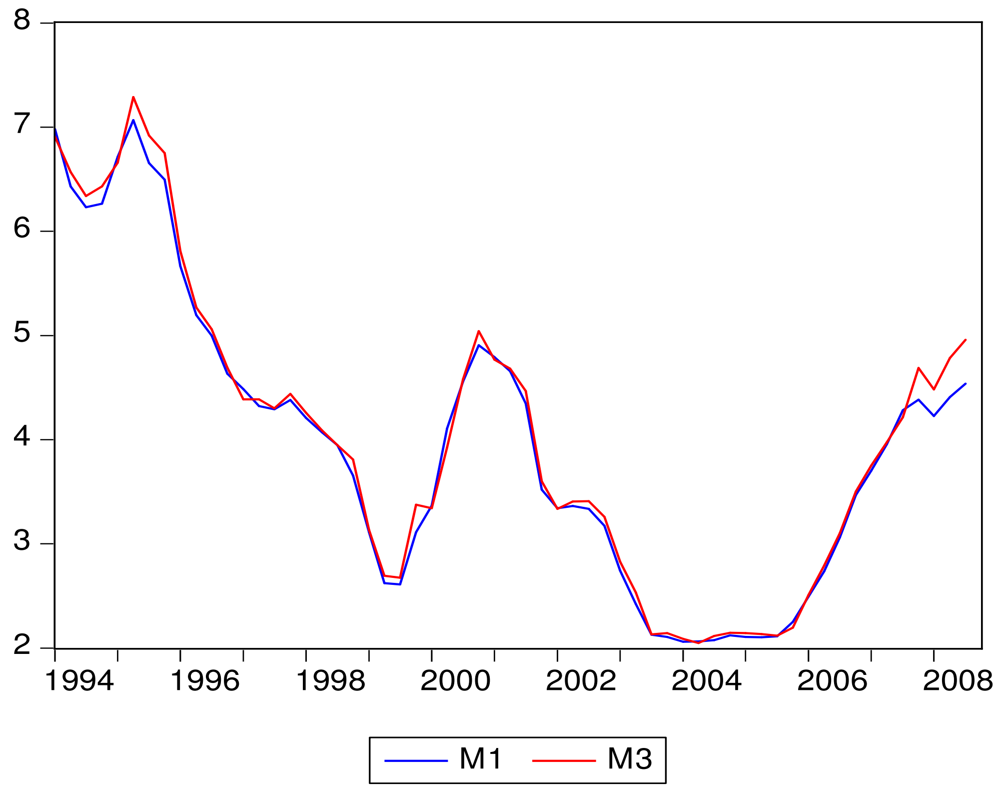

Figure 4. Long Term Interest Rates

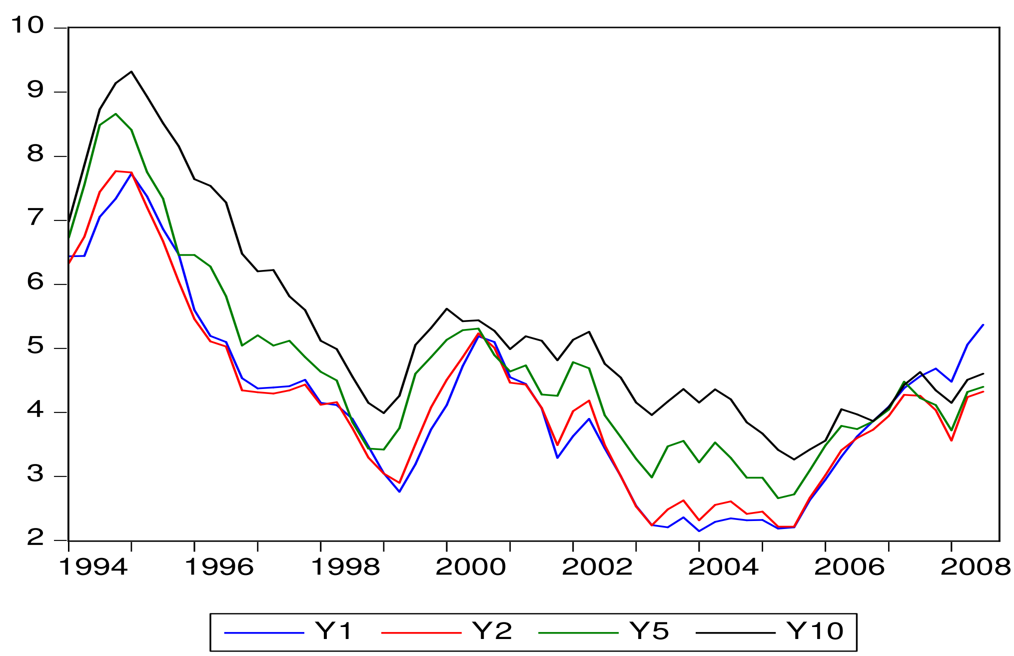

Figure 5. EU15 Unemployment Rate

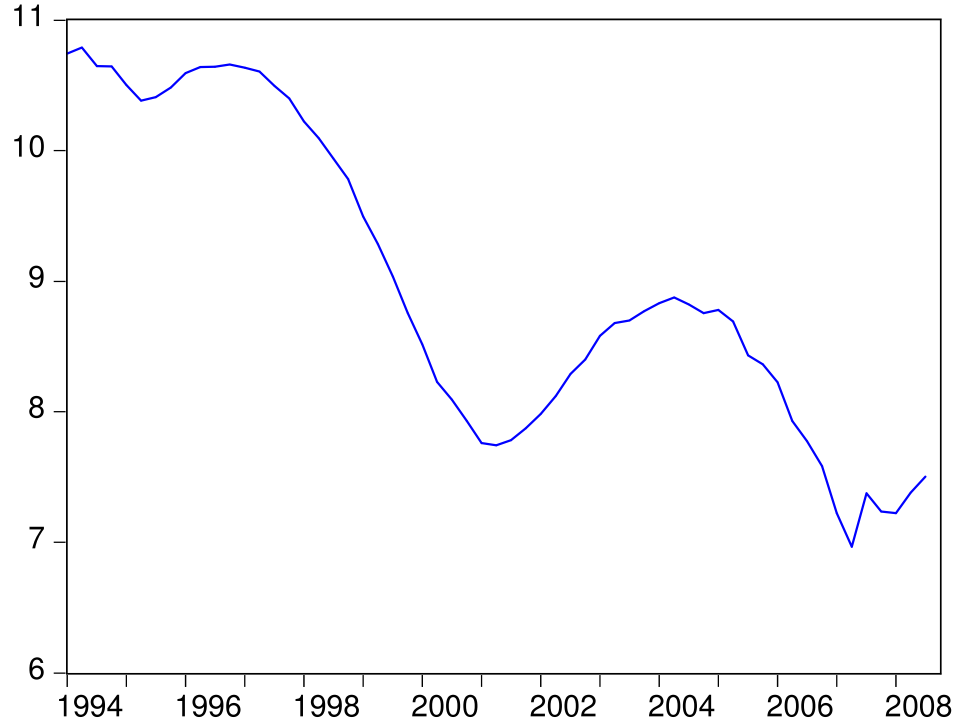

Figure 6. London, Frankfurt and Paris Composite Stock Index

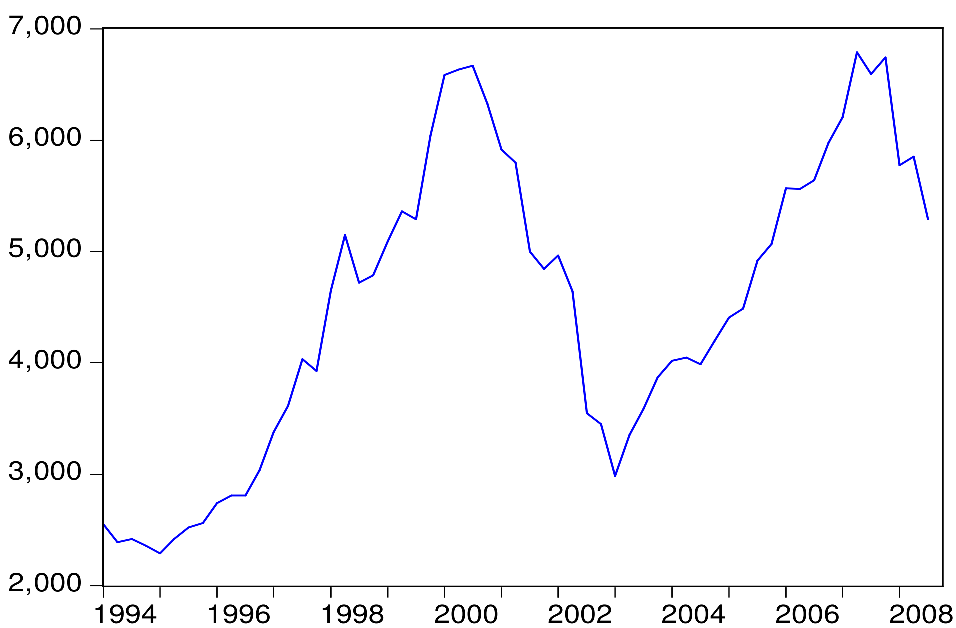

Figure 7. GDP Cyclical Component and Forecasted Probability