Predictive power of the term structure of interest rates over recessions in Europe

Abstract

This work intends to infer for European countries the extent that anticipations of the term structure of interest rates has over recessions, as measured by factor models. For that, we model the shape of the yield curve by latent factors corresponding to its level, slope and curvature. The simple and modified probit and logit models are used to examine the yield curve's ability to forecast economic downturns (recessions). Despite official recessions dates being available at the Centre for Economic Policy Research (CEPR), which recently formed a committee to set the dates of the Euro area business cycle in a manner similar to the NBER, these are based on aggregate data. So, we determine the recessions using the BBQ methodology to have them dated for each individual country in the sample. The findings suggest that the yield curve components predict recessions for more than one year ahead, with increased goodness of fit when the autoregressive term is included as explanatory variable. These results are consistent for both UK, Germany and Portugal.

Keywords: Term structure of interest rates; Prediction; Recessions; European countries; Factor models decomposition

1. Introduction

In finance, modelling the term structure of interest rates has long been an important aspect. Significant efforts have been placed on creating an accurate model for the estimation of the yield curve. By extension, a model to successfully forecast the term structure of interest rates or the yield curve modelling is that of Nelson and Siegel (1987) and it's many extensions (Diebold and Li, 2006). Moreover, simple financial indicators like interest rates and stock prices were showed to often do better than composite indices of leading indicators in predicting economic recessions (Estrella and Mishkin, 1996), especially beyond one quarter periods.
Despite the fact that the term spread (the difference between the yields on long-term and short term treasury securities) has been found useful for forecasting output growth, inflation, industrial production, consumption and recessions (Wheelock and Wohar, 2009) there are other useful avenues to prove this relationship, like the components estimation of this term structure of interest rates based on factor models. Yield curves are thus modelled using the Diebold and Li (2006) dynamic interpretation of the Nelson Siegel model where the three factors are representative of the level, slope and curvature of the curve. The Nelson Siegel model is a parametric parsimonious model for the estimation of the yield curve. Being a three factor model that provides the flexibility to represent the typically observed monotonic, humped and S-shaped curves. It continues

to be one of the principle models used in finance for the estimation of the yield curve. From 1996 onwards, participating central banks have been reporting their yield curve estimates and estimation methods to the bank for international settlements (Shaw et al., 2014) based on this model. However, its dynamic nature as come into force with the work developed by Diebold and Li (2006).

The yield curve reflects both long and short term rates of return offered by securities, reflecting the yield spread of government issued bonds of different maturities. Yield curve predictions about future growth usually appear in two directions. On one hand there is a tentative to predict the growth rate that can be expected at some point in the future and on the other it is tried to predict the probability of recession's occurrence. We adopt the second view here for European markets. For that we use a nonparametric technique, namely the BBQ method to determine recessions in monthly base over the period January 1970 up to December 2012.

Estrella and Mishkin (1998) found the yield curve slope to be a useful recession predictor. If investors begin to suspect that a recession is near, the response of the yield curve will depend on their assessment of the magnitude and duration of the recession's effect on short-term interest rates. Haubrich and Dombrosky (1996) noticed the public anticipated short-term interest rates gradual decline in a recession until the economy's performance improves. These shortenings may stem from countercyclical monetary policy designed to stimulate the economy, or simply the reflection of low real rates of return during the recession. In either case, the anticipated severity and duration of the recession will strongly influence the expected path of short-term interest rates, which will show up in the shape of the yield curve. These effects may even be stronger in European countries, whose assessments are useful in the most recent years.

This work novelty relies on the fact that it is explored here different markets, for a set of European countries (UK, Germany and Portugal), unlike most of the previous literature, applied mostly to the US market. Moreover, for each country it is used data obtained from the yield curve estimation components, the recession periods estimations and their relation in terms of predictable capacity for each country individually. With this amplitude, number of countries, data extension and estimation of recession periods, as far as we are aware, no other study has tried to do previously[1].

This work may be valuable in terms of policy making because the information content of the yield curve may be valuable for the prediction of business cycles, inflation and monetary policy given that the yield curve components are used to infer about their predictability power over economic recessions. Also, the response of the yield curve may be informative about the transmission of monetary policy and, overall, the dynamic impact of shocks on the macro economy. Still, it remained to be seen how incorporating data for the recession that began in 2008 in Europe affects the performance of forecasting models that use factor yields decomposition to predict economic recessions and whether the additional information sheds light on alternative explanations for the forecasting relationship.

[1] Note that this work is part of a current ongoing research considering a higher data set.

The work develops as follows. Section 2 presents a brief literature review over the issue, while section 3 presents the methodology and data used for the analysis. In section 4 results are discussed, while section 5 concludes this work.

2. Literature Review

The term spread or the yield curve slope[2], is for a long considered relevant to forecast business cycles (Wheelock and Wohar, 2009). The ability of the yield curve slope to predict real economic activity has then been put forth by Estrella and Mishkin (1998), for the U.S., and Plosser and Rouwenhorst (1994), in several other industrialized countries. As Wheelock and Wohar (2009) state, *many studies find that the term spread predicts output growth and recessions up to one year in advance, but several also find its usefulness varies across countries and over time* (p. 419). The authors summarize previous papers conclusions by noticing that although many studies find the ability of the term spread to forecast output growth, this importance has diminished over recent years, despite its prevalence as a reliable predictor of recessions. These same studies associate the apparent ability of the term spread to forecast economic activity to actions by monetary authorities to stabilize output growth, given that tightening of monetary policy causes both short and long term interest rates to rise.

Duarte et al. (2005) use aggregate data for the Euro area over the period 1970:1–2000:4, applying linear regression as well as nonlinear models to examine the predictive accuracy of the term spread–output growth relationship. Their results confirm the ability of the yield curve as a leading indicator. Moreover, significant nonlinearity with respect to time and past annual growth is detected, outperforming the linear model in out-of-sample forecasts of 1-year-ahead annual growth. Furthermore, they state that probit models that use the European Monetary Union (EMU) and US yield spreads are successful in predicting EMU recessions. Several authors have related the term structure of interest rates with macroeconomic variables, using both observable and non-observable factors. Ang et al. (2008) proposed a model using the inflation rate as an observable variable and two more latent factors. Rudebusch and Wu (2008) used two observable variables: GDP, inflation and two latent variables. Ang et al. (2006) used only observed variables, although the dependent variable consisted only of short term interest rates.

The first works developed have focused mainly on the slope of the yield curve shape to forecast output or inflation. However, authors set a priori a number of possible lead horizons for the dynamic relation between the yield curve and the macro variables. Only scarcely these studies allowed for bidirectional relations (Stock and Watson, 1989; Estrella and Hardouvelis, 1991). Many papers, like Chauvet and Potter (2005), Benati and Goodhart (2008), and Rudebusch and Williams (2009), used empirical proxies for the slope. Others as Estrella et al. (2003) and Giacomini and Rossi (2006) used empirical proxies also for the level and curvature that roughly account for the shape of

[2] Usually, but not always, measured as the difference between zero-coupon interest rates of 3-month Treasury bills and 10-year Treasury bonds.

the yield curve. In this cases, the identification of changes in the relation between the yield curve and the macro economy was based on structural break tests.
With arbitrage free models (Ang et al., 2006) and with the Nelson and Siegel (1987) decomposition of the yield curve (Diebold et al., 2006) previous studies specified macro finance models, modelling the shape of the yield curve with a set of latent factors (Aguiar-Conraria et al., 2012) that try to distill the whole information of the curve, at each period of time, into factor like level, slope and curvature. By using vector autoregressive models, these models enabled the study of the relationship between the yield curve and the main macroeconomic variables by assessing bidirectional feedbacks with some flexibility and with the assessment of time variation using time varying vector autoregressive models (Mumtaz and Surico, 2009; Bianchi et al., 2009). More recently, Aguiar-Conraria et al. (2012) adopt a time frequency framework in the study of the relation between the yield curve and the macro economy. They study the relation between the level, slope and curvature of the yield curve and macroeconomic activity, inflation and the policy interest rate, in the U.S., across time and frequencies, using the wavelet power spectrum, coherency and phase difference. The authors did not found evidence of a significant role for the curvature either as a leading or as a coincident indicator of economic activity, nor did they found a clear-cut relation between the curvature and inflation. However, during the conundrum, the curvature and the slope were good predictors of the fed funds rate, which indicates that the yield curve may have failed to forecast economic activity but not monetary policy. Also Gallegati et al. (2014) use wavelet analysis to explore the information content of several interest rate spreads for future output growth. The ‘‘scale-by-scale’’ regression analysis shows that standard indicators of the stance of monetary policy, such as the shape of the yield curve, the real federal funds rate, and the credit spread have different information content for future output at different time frames.
Previously, the ability of the yield curve slope to predict real activity or inflation has been assessed with two classes of regression models: discrete (binary) regression models, in which the dependent variable corresponds to a state of recession or expansion (or to a state of inflation pressure or no pressure); continuous dependent variable models, in which the dependent variable is the growth rate of real output (or changes in the rate of inflation). Authors like Estrella et al. (2003) and Rudebusch and Willliams (2009) test and compare the stability of both models.
It has been shown that the yield slope has a good record in forecasting recessions in real-time (Estrella and Trubin, 2006), having marginal predictive power for U.S. recessions over the Survey of Professional Forecasters (Rudebusch and Williams, 2009). In the context of more complex dynamic models and iterative forecasting procedures (Kauppi and Saikonen, 2008), the relevance of the yield slope has survived and has even been reinforced.
Vasicek (1977) and Cox et al. (1985) developed no arbitrage models for the short term interest rate. The disadvantage of these models was their low performance in predicting future term structures of interest rates. After, Longstaff and Schwartz (1992) created a two factor models where the first was associated to the short term interest rate and the second to its short term volatility. Balduzzi et al. (1996) extended the previous authors,

developing a three factor model adding the short term rates average. Litterman and Scheinkman (1991) developed a three factor model where the first corresponded to the zero coupon interest curve level, the second to its slope and the third to the yield curvature. Previous empirical results prove that there are needed at least three factors in order to be possible to capture the different shapes of the yield.

With respect to parametric models, both static and dynamic models have been developed to model the yield. Nelson and Siegel (1987), Björk and Christensen (1999) and Svensson (1994) created static models. The firsts developed a three factor model which may be interpreted as components which explain the level, slope and curvature of the yield curve. The seconds added a second factor of slope to the first model to improve the modelling of short term maturities. The last created a model with a second curvature model to the long point of the North American curve.

After a new interpretation, Diebold and Li (2006) developed a class of dynamic models of three factors based in the Nelson and Siegel (1987) model to shape the yield, period by period. This variables could be read as level, slope and curvature of the yields.

Caldeira et al. (2010) used the Nelson and Siegel (1987) and Diebold and Li (2006) models with the goal of estimating the yield in the Brasilian market. The estimation has been made using the Kalman filter and the authors concluded, based on the value of the standard average error, that this method generates better predictions than the two step procedures used by Diebold and Li. Christensen et al. (2011) further developed a class of no arbitrage models based on the Nielsen and Siegel (1987) methodology.

Diebold et al. (2006) developed a model with the coexistence of latent and observable macroeconomic variables. The authors based their explanation in the three factor model of Nielsen and Siegel (1987) and in the vector autoregressive model (VAR) to model the macroeconomic factors. After, Huse (2007) proposed a model where the yield curve was explained only through observable macroeconomic variables. This model presented advantages and disadvantages when compared with the rest of the models: the number of parameters to be estimated did not increased with the curve vertices. The estimation of the model by least squares was quite precise and contrarily to most of the previous literature, was based on data with transversal cuts and time series.

Nelson and Siegel (1987) used data from North American titles between 1981 and 1983. The model was capable to explain 96% of the variations of the zero curves. The authors also found a high correlation between the present value of long term yields in the adjusted curve and the real prices reported in the market. In this sense, conclude that the model was able to capture different attributes of the relationship between the interest curve with zero coupon and the curves maturity. The Diebold and Li (2006) model was able to capture to capture the different forms of the yield curves (ascending slope, descending or twisted). Diebold et al. (2006) used treasury bill yields from the US with maturities of 3, 6, 9, 12, 15, 18, 21, 24, 30, 36, 60, 72, 84, 96, 108 and 120 months between January 1972 and December 2000. The macroeconomic variables used were: production capacity (economic activity), the basic interest rate from the North American market (instrument of monetary policy) and the inflation rate (the consumer price index). The authors conclude that the level factor is highly correlated with inflation and that the slope factor is highly correlated with the economic activity. The curvature factor did not presented any relation with any macroeconomic variable.

Huse (2007) used the following data from the US economy: monthly fees of U.S. securities from January 1970 to December 2003, macroeconomic variables of inflation (CPI), economic activity (GDP and unemployment rate), monetary policy (basic interest rates of the US central Bank) and fiscal policy (government debt). He concluded that the level, slope and curvature of the curve is explained by inflation (CPI), monetary policy (prime rate) and economic activity (unemployment rate) respectively. Moreover, this model overcame the latent variables when considering the recessions during the period 1970-2003. The methodology used was to compare the estimates based on the criterion of Mean Absolute Error. According to Huse, models with latent variables hardly captured the inversions in the Term Structure of Interest Rates, which could occur during periods of recessions.

The Euro area was created on January 1st, 1999 and a single currency in circulation entered in force as of January 1st, 2002. In this moment there was the need to establish the tradition of dating recessions. This has been performed by the Centre for Economic Policy Research (CEPR)[3] which formed a committee to set the Euro area business cycle dates similarly to NBER. The Committee decided to date these in terms of quarters and not months, but being aware that there is scarcity of appropriate historical monthly time series for several European countries, it would be more useful to establish a monthly business cycle chronology for the Euro area, which will be explained in the next section.

With respect to the Euro area, Moneta (2005) paper studies the informational content of the slope of the yield curve as a predictor of recessions in the euro area and provides evidence of the potential usefulness of this indicator for monetary policy purposes. The historical predictive power of ten variations of yield spreads, for different segments of the yield curve, is tested using a probit model. The yield spread between the ten-year government bond rate and the three-month interbank rate outperforms all other spreads in predicting recessions in the euro area. The forecast accuracy of the spread between ten-year and three-month interest rates is also explored in an exercise of out-of-sample forecasting. This yield spread appears to contain information beyond that already available in the history of output, and to outperform other competitor indicators. Still, the authors use the yield spread to predict recessions and not the yield curve components as most of the studies do, but applied to the US market, despite their improved proved results over the yield spread.

For Europe, previous research findings confirm the predictive power of the yield curve demonstrated for the US. Estrella and Mishkin (1997) examined the predictive power of the yield spread in France, Italy, Germany and the UK using data from 1973:Q1 until

[3] The Committee defines a recession as a significant decline in the level of economic activity, spread across the economy of the euro area, usually visible in two or more consecutive quarters of negative growth in GDP, employment and other measures of aggregate economic activity for the euro area as a whole, and reflecting similar developments in most countries ("Business Cycle Dating Committee of the Centre for Economic Policy Research", CEPR, September 2003). To make sure that expansions or recessions are widespread over the countries of the area, the CEPR bases its judgment on euro area aggregate statistics as well as country statistics.

1994:Q4, suggesting that the yield curve significantly predicted real economic activity four to eight quarters ahead. For France, Germany and Italy over the period 1970:Q1 to 2002:Q2, Moneta (2005) found that the yield curve forecasting power was strong in the 1970's and 1980's but lesser in the 1990's. These findings of the diminishing predictive power of the yield curve were in accordance to those of Dombrosky and Haubrich (1996) for the United States. Analyzing the predictive power of the yield curve for several countries, including France, Canada, Italy, Germany, Japan, Sweden, Netherlands, UK and the US from 1970 to 2008, Chinn and Kucko (2009) conclude that the yield spread contains significant power when forecasting industrial production growth over a one-year time horizon, also finding evidence that the yield curve predictive power seemed to be declining over time, although with some exceptions.

Chinn and Kucko (2010) find that the predictive power of the yield curve has deteriorated in recent years, but that there is reason to believe that European country models perform better than non-European countries when using more recent data. They even show that the yield curve proves to have predictive power even after accounting for other leading indicators of economic activity. The authors restrict their analysis to Canada, France, Germany, Italy, Japan, the Netherlands, Sweden, the United Kingdom and the United States. Further, they estimate an aggregate Euro Area specification using data from 1990-2009.

Erdogan et al. (2014) extend the benchmark Estrella and Hardouvelis (1991) term spread approach to recession forecasting by including the stock market macro liquidity deviation factor. They use a probit framework to predict recessions, as defined by the NBER between 1959Q1 and 2011Q4, to conclude that combining the yield curve parameter with the stock market liquidity deviation significantly improves our ability to predict the onset of a US recession, based both on in-sample and out-of-sample tests. In addition, changes in stock market depth further increase the accuracy of the model. The authors suggest that economic forecasters and those charged with conducting economic stabilization policy more generally would benefit from monitoring not only the yield curve but also stock market depth and liquidity, and their deviation from one another.

From the literature review presented, much more needs to be inferred for European countries in terms of yield curve components influence over recessions. Moreover, the dating of these recessions are only to be compared here with the CEPR data, where we have adopted the view of their proper estimation and in accordance to each individual country data specifications.

3. Data and Methodology

Our data sample comprises yields of different maturities whose data has been collected from the central banks of each of the European countries under analysis, namely United Kingdom, Germany and Portugal for the general period starting in January 1970 and ending in December 2012. Data to determine the yield curve components respects daily data of yields of different maturities which have been transformed into monthly series by adopting the last available data in a given month. To determine recession periods, data of real GDP has been collected in quarterly terms from the OECD and previously transformed into monthly series, by a method which will be after explained.

Unlike many of the previous literature, we take here a different approach, not analyzing the difference between short and long term interest rates (yield spread) but having into account the three factor models decomposition of the term structure of interest rates. As such, we start by estimating the components shape of the term structure of interest rates through the Diebold and Li model, after by applying the algorithm BBQ to estimate expansion and recession periods, and after joining steps 1 and 2 using the probabilistic models logit and probit to estimate the coefficients and the adjustment curves between both.

Nelson and Siegel (1987) propose a parametric parsimonious 3 factor model for modelling the term structure of interest rates. They propose their forward rate curve as,

$$f_t(\tau) = \beta_{1t} + \beta_{2t} e^{-\lambda_t \tau} + \beta_{3t} \lambda_t e^{-\lambda_t \tau} \tag{1}$$

This function consists in a constant plus a polynomial times an exponential decay term, being a class of approximating functions (Courant and Hilbert, 1953). The solution to the second order differential equation is the approximating forward curve with equal roots for the spot rates (Shaw et al., 2014). So, the corresponding yield curve for the Nelson Siegel forward rate curve is given by,

$$f_t(\tau) = \beta_{1t} + \beta_{2t} \frac{1 - e^{-\lambda_t \tau}}{\lambda_t \tau} + \beta_{3t} \frac{1 - e^{-\lambda_t \tau}}{\lambda_t \tau} - e^{-\lambda_t \tau} \tag{2}$$

Here λ_t represents the time decay parameter, τ the maturity and β_{1t}, β_{2t} and β_{3t} the three Nelson Siegel parameters, which may be viewed as the long, medium and short term components of the yield curve, and the factor loadings on these parameters give an explanation to why this is so. For example, the factor loading on the parameter β_{1t} is 1[4]. The factor loading on β_{2t} represents the short term factor, with a factor loading given by $\left(1 - e^{-\lambda_t \tau}\right) / \lambda_t \tau$[5]. Finally, β_{3t} represents the medium term factor with a factor loading of $\left(1 - e^{-\lambda_t \tau} / \lambda_t \tau\right) - e^{-\lambda_t \tau}$[6]. In equation (2) λ_t parameter is a time constant determining the rate at which the regressor variable decays to zero[7].

In 2006, Diebold and Li provided insights to how these three factors can also be interpreted as the level (long component), slope (short component) and curvature (medium component) of the curve. The long term component β_{1t} is the same for all maturities, being equal to 1. Thus, any increase in the component will cause the whole curve shift upwards turning it able to see that this factor represents the level of the curve. With respect to the short-term factor β_{2t}, it can be seen as the slope of the curve,

[4] As this is a constant, it does not decay to 0 and will be the same for all maturities, being thus the long term factor.

[5] This one starts at 1 but decays quickly at an exponential rate to 0.

[6] Begins at 0 and then increases before decaying to 0, causing the hump in the yield curve.

[7] Small values for this parameter result in small decays and a better fitting of longer maturities. Large values of it result in fast decays, fitting better the short maturity curves. This parameter also governs where the β_{3t} factor loading reaches it maximum.

given that an increase in this component will cause the short rates to increase more than long rates as the short rates load more heavily on β_{2t}, thus changing the curves slope. With respect to the medium component, it is closely related to the curvature of the curve, given that long and short term maturities do not load heavily on it, but as β_{3t} increases, also the curve for medium maturities increases, thus increasing its curvature. While some authors prefer to use empirical proxies to these factors, we prefer the latent factors approach, as do Aguiar-Conraria et al. (2012), because it is based on a formal model, turning easier economic interpretations, and also by allowing the use of the information across the whole yield maturities.

To fit the yield curve to the Nelson and Siegel model we could estimate the β parameters and λ using nonlinear least squares for every observation t. But, due to its complexity, an alternative methodology proposed by Nelson and Siegel (1987) may be applied, also followed by Shaw et al. (2014). This consists in setting the parameter λ_t to a predefined fixed value, allowing us to compute factor loadings. After, using ordinary least squares regressions we estimate beta values for each day t. However, to set up an appropriate value for parameter λ_t we follow Diebold and Li (2006) by selecting the average yields maturity to represent the medium term rate and recalling that the parameter λ_t governs where the β_{3t} factor loading reaches its maximum, enabling us to choose the parameter λ_t value that maximizes the loading on the medium term factor. So, the ordinary least squares regression can then be performed on the daily yield data, resulting in a time series of estimates of the β parameters and their corresponding residuals.

So, like in Diebold et al. (2006) and Aguiar-Conraria et al. (2012) we assume that the β's follow a vector autoregressive process of first order, allowing casting the yield curve latent factor model in state-space form and using the Kalman filter to compute maximum-likelihood estimates of the hyper-parameters and the implied estimates of these same β time varying-parameters. For more details over the state-space model, comprising both the transition and the measurement systems, relating a set of N observed zero-coupon yields of different maturities to the three latent factors we suggest the reading of Diebold et al. (2006) and Aguiar-Conraria et al. (2012). Moreover, following the authors we also assume that the innovations of the measurement and of the transition systems are white noise and mutually uncorrelated, with the variance covariance matrix of the innovations to the measurement system assumed to be diagonal. This assumption means that the deviations of the observed yields from those implied by the fitted yield curve are uncorrelated across maturities and time[8]. More can be found about this estimation in Diebold et al. (2006) and Aguiar-Conraria et al. (2012).

As explained previously, the reliability of quarterly based definitions of business cycles may be insufficient to explain the yield curve components influence over recessions. Dating business cycles at the monthly level is likely to provide a more precise information about the exact turning points than quarterly dating. Moreover, since the state of the economy is an important variable in empirical models, applications are

[8] Given the large number of observed yields used, this is necessary for computational tractability.

conceivable which would require knowledge about the business cycle turning points of the Euro area on a monthly basis. Applying the highest diligence in interpreting the available data we set up a monthly business cycle chronology for the Euro area based on the BBQ method and following Mönch and Uhlig (2005).

To determine recessions we use the BBQ method which is a non-parametric method, using the principles of Bry and Boschan (1971) underlying much of the NBER business cycles dating philosophy. Being Y_t a series representing aggregate economic activity and setting $y_t = \log(Y_t)$, in the BBQ method a local peak occurs at time t if y_t is greater than y_{t+k} with k = 1, 2, …, K, and a local though occurs at time t if y_t is lesser than y_{t+k}, with k = 1, 2, …, K, being K generally fixed to be 5 if monthly series are used. To eliminate local peaks and though, we need a set of rules. The principle criteria is that a phase must last at least 6 months and a complete cycle should have a minimum duration of 15 months. A recession would be the time between peak and though, such that the use of five months and other criteria do not allow to call recession too often (Harding and Pagan, 2002; Pagan, 2010). In accordance to Harding and Pagan (2002) four items are needed to provide useful information for inspecting a cycle which are: the duration of the cycle and its phases; the amplitude of the cycle and its phases; any asymmetric behavior of the phases; and cumulative movements within the phases. We employ the BBQ method to determine recession periods between 1970:M1 to 2012:M12 in an individual country way.

To reach this goal and given that GDP data respects to quarterly observations we follow Mönch and Uhlig (2005), where two different procedures may be followed. First we need to turn softer the data or to interpolate the real quarterly GDP data with a non-parametric estimation (the cubic spline) and then turning points are detected by the BBQ algorithm. We adopt this approach in the current work. In fact, the present work is part of a much higher work including several other European countries, besides the euro area, where it will be used both ways of transforming GDP quarterly data into monthly data, currently under development. So, a second possibility is to perform the dating based on the quarterly data collected and assuming the observation in the middle of the quarter in the turning points computation (assuming the middle of the quarter as the month were the cycle starts).

We need to keep in mind that the dating of the cycles and the yield curve components are not observable but yes estimated. As such all is subject to the change of criterion character change which could obviously influence the conclusions to be taken. However, and considering the BBQ method of recession dates (business cycle turning points) identification, even if estimated, these have always been compared to the CEPR provided data periods in order to improve the reliability of the estimated dates. The advantage is that this way guarantees the identification of specific recession points in time for each country under analysis and considering that each is an individual nation inside the larger group of the European Union.

As in Estrella and Mishkin (1998), we use a recession dummy as the dependent variable to focus on the timing of recessions. Previously, Estrella and Mishkin (1996) use a probit model to predict a recession dummy variable, R_t, where it equals 1 if the economy is in recession in period t and 0 otherwise. Choosing to forecast a recession rather than output growth has a goal. Information on the predictability of the strengths of recoveries and expansions with information on the timing of recessions would be mixed if used a goodness-of-fit measure for a model of output growth. By using a recession dummy variable, we are able to isolate the accuracy with which one can predict the date of the onset and the expected length of recessions.

Estrella and Mishkin (1996) obtain a quantitative measure of fit with the pseudo R^2 showing that, among the variables they study, the yield curve slope is the single most powerful predictor of recessions for forecast horizons beyond one quarter, but still the authors use the spread instead of the yield curve components decomposition as we do here.

The simple probit model assumes independent and evenly distributed error terms around the mean of zero. Duecker (1997) points out that this assumption is not plausible since for time series data the error terms might be highly correlated. This led to the development of the modified probit model which adds a lag of the dependent variable to its simplest version in order to remove any possible serial correlation in errors. We have also used the simple and the modified logit model for robustness check and as we will be able to see after, the logit model does not bring additional benefits as the use of the probit, only confirming results robustness.

When comparing the goodness of fit for non-linear model the standard and adjusted R^2 is no longer a suitable measure. With this in mind, Estrella and Mishkin (1996) suggested an alternative method for measuring the goodness of fit for non-linear estimated equations corresponding to the coefficient of determination in a standard linear regression model. This measure became known as the pseudo R^2 and can be represented as

$$\text{Pseudo R}^2 = 1 - \left(\frac{L_n}{L_c}\right)^{-\left(\frac{2}{N}\right)\log L_c} \tag{3}$$

Being Ln the value of the log-likelihood of the estimated model (the unrestricted maximum value of the likelihood function), Lc is the value of a constrained model containing only the constant term (the maximum value of the constraint likelihood function that all coefficients except the constant are zero) and N the number of observations in the model. Estrella and Mishkin (1996) mention that this function ensures that the values 0 and 1 correspond to no fit and perfect fit respectively. The pseudo R^2 is used together with the estimated coefficient probabilities and z-statistics in order to infer the correct lag which produces the best model fit for all the studied variables (Aziakpono and Khomo, 2007).

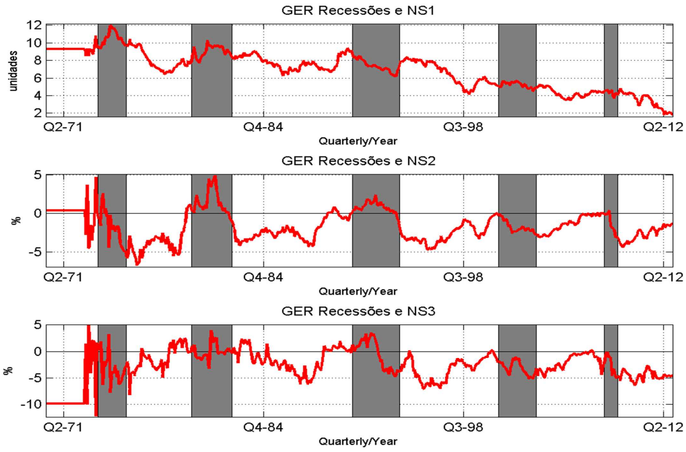
The simple and modified probit and logit models were estimated using the yield curve components as the explanatory variables besides the autoregressive variable for the modified versions with forecasting horizons ranging from 1 to 18 months ahead. The statistical significance of the estimated coefficients is measured by the z-statistic and probability statistic in both model versions to be able to determine the explanatory power of the yield curve components over European recessions. Notice that the optimal forecast horizon is determined at the lag length which produces the highest pseudo R^2.

In the following section we will present all the estimation results for the 3 countries here analyzed.

4. Empirical Results

This section presents the data obtained through the three step estimation procedure adopted in the current study.

Figure 1: Germany Recessions and yield curve components estimated evolution



Note: This figure presents Germany recession identified periods through the BBQ methodology in grey and its three yield curve components evolution (the red line plot). The first plot refers to the level, the second to the slope and the third to the curvature The data period considered goes from January 1970 until December 2012. Values in the y axis refer to unities (for the level plot) and to percentage terms for both the slope and curvature

We start by presenting the plot of the yield curve components estimation for the German case, one plot for each of the components and by order: the level, the slope and the curvature.

As we are able to observe the component representing the slope always increases previous to a given recession. This also happened for the level and curvature until the 90s where an inverse pattern starts to be observed from that moment onwards. Still, the level decreases even more in recent years, while the slope and the curvature remained at negative percentage values from the year 1990 onwards.

We go one step further and start now presenting the estimated coefficients for the three countries under analysis, the pseudo R^2 and the restricted log likelihood value in tables 1 to 8. The first four tables are referred to the UK market and in order: considering the simple probit estimation, the simple logit estimation, the augmented probit and finally the augmented logit (tables 1 to 4) considering prediction periods from 1 up to 18 months.

Table 1: Simple Probit Estimates of the Probability of Recession – UK

	consta	b1	b2	b3	PsR2	LogL
h=1	−1.718***	0.060***	0.145***	−0.180***	0.138	−204.890
	(0.20)	(0.02)	(0.03)	(0.03)		
h=2	−1.754***	0.062***	0.170***	−0.199***	0.138	−200.145
	(0.20)	(0.02)	(0.04)	(0.03)		
h=3	−1.832***	0.063***	0.210***	−0.239***	0.174	−191.586
	(0.21)	(0.02)	(0.04)	(0.03)		
h=4	−1.851***	0.063***	0.239***	−0.255***	0.192	−187.211
	(0.21)	(0.02)	(0.04)	(0.04)		
h=5	−1.882***	0.063***	0.270***	−0.274***	0.214	−181.907
	(0.21)	(0.02)	(0.04)	(0.04)		
h=6	−1.892***	0.065***	0.288***	−0.277***	0.225	−179.407
	(0.21)	(0.02)	(0.04)	(0.04)		
h=7	−1.864***	0.067***	0.285***	−0.259***	0.216	−181.207
	(0.21)	(0.02)	(0.04)	(0.04)		
h=8	−1.84***	0.07***	0.28***	−0.24***	0.21	−182.28
	(0.21)	(0.02)	(0.04)	(0.04)		
h=9	−1.74***	0.07***	0.24***	−0.19***	0.17	−190.53
	(0.21)	(0.02)	(0.04)	(0.03)		
h=10	−1.66***	0.07***	0.22***	−0.15***	0.15	−196.71
	(0.20)	(0.02)	(0.04)	(0.03)		
h=11	−1.59***	0.07***	0.20***	−0.11***	0.12	−201.80
	(0.20)	(0.02)	(0.03)	(0.03)		
h=12	−1.54***	0.07***	0.20***	−0.09***	0.12	−202.60
	(0.20)	(0.02)	(0.03)	(0.03)		
h=13	−1.50***	0.07***	0.20***	−0.07**	0.11	−204.55
	(0.20)	(0.02)	(0.03)	(0.03)		
h=14	−1.43***	0.06***	0.19***	−0.04	0.10	−206.75
	(0.20)	(0.02)	(0.03)	(0.03)		
h=15	−1.39***	0.06***	0.18***	−0.03	0.09	−208.53
	(0.20)	(0.02)	(0.03)	(0.03)		
h=16	−1.34***	0.06***	0.15***	−0.02	0.07	−212.70
	(0.20)	(0.02)	(0.03)	(0.03)		
h=17	−1.29***	0.05**	0.14***	−0.01	0.06	−215.84
	(0.20)	(0.02)	(0.03)	(0.03)		
h=18	−1.24***	0.05**	0.12***	−0.00	0.05	−218.27
	(0.20)	(0.02)	(0.03)	(0.03)		

Notes: This table presents simple probit estimated coefficients. Consta refers to the constant term, b1 to the level component, b2 to the slope and b3 to the curvature component of the yield curve estimated. The dependent variable is a binary variable which accounts for 1 if there is a recession period and 0 otherwise. PsR2 refers to the pseudo R^2 estimate, while LogL is the log likelihood estimate under the restricted model. Finally h represents the forecasting periods which go from 1 until 18 months. The estimated standard errors are in parentheses. ***,**,* indicate significance at the 1, 5 and 10 % significance levels, respectively. The sample observations are in monthly terms and the period of the estimation runs from 1970:M1 until 2012:M12.

Considering the probit estimations for the UK market we may state that all yield curve components estimates remain significant up to month 13 of prediction, while both the level and the slope remain significant up to 18 months. As such, for 1 year and a half forecasting horizon, both the slope and the level of the yield curve remain significant but the coefficient of the curvature becomes insignificant and ads noting to the goodness of fit. Moreover, both the constant term and the curvature have a negative coefficient. The negative sign implies that as the yield curvature decreases, the likelihood of recession increases. The goodness of fit measure (the pseudo R^2) indicates that it is relatively high until 8 months of forecasting period and it starts decreasing in the 7th forecasting month period. Results remain practically unchanged when we use the simple logit model instead of the probit. Table 2 presents all coefficients estimates for this case.

Table 2: Simple Logit Estimates of the Probability of Recession – UK

	consta	b1	b2	b3	PsR2	LogL
h=1	−2.921***	0.103***	0.267***	−0.316***	0.136	−205.322
	(0.36)	(0.04)	(0.06)	(0.06)		
h=2	−2.996***	0.105***	0.310***	−0.351***	0.136	−200.621
	(0.37)	(0.04)	(0.06)	(0.06)		
h=3	−3.137***	0.108***	0.373***	−0.415***	0.170	−192.613
	(0.38)	(0.04)	(0.07)	(0.06)		
h=4	−3.173***	0.108***	0.419***	−0.442***	0.187	−188.390
	(0.38)	(0.04)	(0.07)	(0.07)		
h=5	−3.224***	0.108***	0.472***	−0.478***	0.209	−183.178
	(0.39)	(0.04)	(0.07)	(0.07)		
h=6	−3.222***	0.108***	0.507***	−0.488***	0.220	−180.583
	(0.39)	(0.04)	(0.07)	(0.07)		
h=7	−3.165***	0.110***	0.503***	−0.459***	0.212	−182.261
	(0.39)	(0.04)	(0.07)	(0.07)		
h=8	−3.13***	0.11***	0.51***	−0.44***	0.21	−182.90
	(0.39)	(0.04)	(0.07)	(0.07)		
h=9	−3.00***	0.12***	0.45***	−0.36***	0.18	−190.24
	(0.38)	(0.04)	(0.07)	(0.06)		
h=10	−2.86***	0.12***	0.42***	−0.29***	0.15	−195.63
	(0.38)	(0.04)	(0.07)	(0.06)		
h=11	−2.73***	0.12***	0.39***	−0.21***	0.13	−200.75
	(0.38)	(0.04)	(0.06)	(0.06)		
h=12	−2.66***	0.12***	0.39***	−0.18***	0.12	−201.53
	(0.38)	(0.04)	(0.06)	(0.06)		
h=13	−2.59***	0.12***	0.37***	−0.12**	0.12	−203.53
	(0.38)	(0.04)	(0.06)	(0.06)		
h=14	−2.50***	0.12***	0.35***	−0.07	0.11	−205.51
	(0.38)	(0.04)	(0.06)	(0.06)		
h=15	−2.42***	0.11***	0.34***	−0.04	0.10	−207.21
	(0.37)	(0.04)	(0.06)	(0.05)		
h=16	−2.33***	0.11***	0.30***	−0.02	0.08	−211.35
	(0.37)	(0.04)	(0.06)	(0.05)		
h=17	−2.22***	0.09**	0.26***	−0.01	0.06	−214.59
	(0.36)	(0.04)	(0.05)	(0.05)		
h=18	−2.13***	0.08**	0.24***	−0.00	0.05	−217.05
	(0.36)	(0.04)	(0.05)	(0.05)		

Notes: This table presents simple logit estimated coefficients. Consta refers to the constant term, b1 to the level component, b2 to the slope and b3 to the curvature component of the yield curve estimated. The dependent variable is a binary variable which accounts for 1 if there is a recession period and 0 otherwise. PsR2 refers to the pseudo R^2 estimate, while LogL is the log likelihood estimate under the restricted model. Finally h represents the forecasting periods which go from 1 until 18 months. The estimated standard errors are in parentheses. ***,**,* indicate significance at the 1, 5 and 10 % significance levels, respectively. The sample observations are in monthly terms and the period of the estimation runs from 1970:M1 until 2012:M12.

The first thing to notice from table 2 is that our main conclusions taken for table 1 remain unchanged both in terms of significance and in terms of coefficients sign. Also in the logit case the positive values obtained for the components estimates of the yield curve in the UK for both the level and the slope are positive and so as the yield spread and level increase the likelihood of recession increases. Still, both level and slope are very important components to explain recessions in the UK and not only the slope as argued by many authors. Moreover, the positive coefficient sign obtained also contradicts some previous literature findings stating that the slope coefficient is negative, meaning that while the yield spread decreases the likelihood of recession's increases.

Tables 3 and 4 present the estimates for the UK market of the augmented probit and logit models respectively. If we have already concluded that the logit model doesn't add nothing to the estimates, this is even more evident in terms of robustness check when we consider the augmented case, i.e., by including the autoregressive term. The only difference is with respect to the goodness of fit measure which increases when we consider the lag recession as an independent variable in the estimates.

Table 3: Probit Estimates of the Probability of Regression - UK [autoregressive Term]

	consta	b1	b2	b3	b4	PsR2	LogL
h=1	−2.823***	0.038	0.179**	−0.161**	3.855***	0.821	−41.554
	(0.45)	(0.04)	(0.07)	(0.07)	(0.31)		
h=2	−2.669***	0.046	0.211***	−0.198***	3.198***	0.706	−68.135
	(0.36)	(0.03)	(0.06)	(0.06)	(0.25)		
h=3	−2.708***	0.056**	0.261***	−0.259***	2.795***	0.631	−85.656
	(0.34)	(0.03)	(0.06)	(0.05)	(0.23)		
h=4	−2.552***	0.057**	0.275***	−0.262***	2.400***	0.553	−103.522
	(0.30)	(0.03)	(0.05)	(0.05)	(0.21)		
h=5	−2.459***	0.058**	0.296***	−0.277***	2.073***	0.494	−117.191
	(0.28)	(0.02)	(0.05)	(0.05)	(0.20)		
h=6	−2.296***	0.058**	0.290***	−0.261***	1.737***	0.430	−131.807
	(0.26)	(0.02)	(0.05)	(0.04)	(0.19)		
h=7	−2.114***	0.056**	0.272***	−0.234***	1.462***	0.366	−146.527
	(0.24)	(0.02)	(0.04)	(0.04)	(0.18)		
h=8	−1.99***	0.06**	0.26***	−0.22***	1.21***	0.31	−158.40
	(0.23)	(0.02)	(0.04)	(0.04)	(0.18)		
h=9	−1.78***	0.05**	0.21***	−0.16***	0.96***	0.24	−175.28
	(0.21)	(0.02)	(0.04)	(0.03)	(0.17)		
h=10	−1.67***	0.05**	0.19***	−0.12***	0.81***	0.19	−186.11
	(0.20)	(0.02)	(0.04)	(0.03)	(0.17)		
h=11	−1.58***	0.05**	0.18***	−0.09***	0.66***	0.15	−194.99
	(0.20)	(0.02)	(0.03)	(0.03)	(0.17)		
h=12	−1.53***	0.06***	0.19***	−0.08***	0.47***	0.13	−199.25
	(0.20)	(0.02)	(0.03)	(0.03)	(0.18)		
h=13	−1.48***	0.06***	0.18***	−0.06**	0.34*	0.12	−202.92
	(0.20)	(0.02)	(0.03)	(0.03)	(0.18)		
h=14	−1.42***	0.06***	0.18***	−0.04	0.21	0.10	−206.15
	(0.20)	(0.02)	(0.03)	(0.03)	(0.19)		
h=15	−1.38***	0.06***	0.18***	−0.03	0.06	0.09	−208.48
	(0.20)	(0.02)	(0.03)	(0.03)	(0.19)		
h=16	−1.35***	0.06***	0.16***	−0.02	−0.09	0.07	−212.60
	(0.20)	(0.02)	(0.03)	(0.03)	(0.20)		
h=17	−1.32***	0.06***	0.15***	−0.02	−0.26	0.06	−215.06
	(0.20)	(0.02)	(0.03)	(0.03)	(0.20)		
h=18	−1.30***	0.06***	0.14***	−0.02	−0.46**	0.06	−215.94
	(0.20)	(0.02)	(0.03)	(0.03)	(0.22)		

Notes: This table presents augmented probit estimated coefficients. Consta refers to the constant term, b1 to the level component, b2 to the slope and b3 to the curvature component of the yield curve estimated. The dependent variable is a binary variable which accounts for 1 if there is a recession period and 0 otherwise. PsR2 refers to the pseudo R^2 estimate, while LogL is the log likelihood estimate under the restricted model. Finally h represents the forecasting periods which go from 1 until 18 months. The estimated standard errors are in parentheses. ***,**,* indicate significance at the 1, 5 and 10 % significance levels, respectively. The sample observations are in monthly terms and the period of the estimation runs from 1970:M1 until 2012:M12.

Considering the added autoregressive term the level yield curve component only becomes significant from the 3rd month of forecasting, while the slope remains significant and positive for all considered forecasting periods. Overall, the spread of the yield curve has predictive power on the recessions up to one year and a half, but the goodness of fit decreases while the forecasting horizon increases. Given that the slope coefficient remains positive for all forecasting horizons we may argue that not even in the face of huge recessions like the recent financial crisis, which has hit many countries including the UK pushing it into a recession, we have the inverted yield curve as argued by many authors in the literature as presented in section 2. As such, the consistent well behaved yield curve can be regarded as an indicator of a not made in UK recession.

Table 4: Logit Estimates of the Probability of Regression - UK [autoregressive Term]

	consta	b1	b2	b3	b4	PsR2	LogL
h=1	−5.743***	0.099	0.381**	−0.346**	7.310***	0.819	−41.947
	(1.08)	(0.09)	(0.16)	(0.15)	(0.73)		
h=2	−5.176***	0.104	0.406***	−0.388***	5.829***	0.703	−68.863
	(0.80)	(0.06)	(0.12)	(0.11)	(0.53)		
h=3	−5.102***	0.115**	0.482***	−0.488***	5.020***	0.627	−86.450
	(0.71)	(0.06)	(0.11)	(0.10)	(0.47)		
h=4	−4.657***	0.107**	0.497***	−0.477***	4.250***	0.549	−104.574
	(0.61)	(0.05)	(0.10)	(0.09)	(0.40)		
h=5	−4.387***	0.104**	0.528***	−0.491***	3.637***	0.488	−118.538
	(0.56)	(0.05)	(0.09)	(0.09)	(0.37)		
h=6	−4.071***	0.101**	0.531***	−0.473***	3.062***	0.427	−132.490
	(0.51)	(0.04)	(0.09)	(0.08)	(0.34)		
h=7	−3.697***	0.093**	0.503***	−0.426***	2.573***	0.365	−146.922
	(0.46)	(0.04)	(0.08)	(0.08)	(0.32)		
h=8	−3.44***	0.09**	0.49***	−0.40***	2.13***	0.31	−158.36
	(0.43)	(0.04)	(0.08)	(0.07)	(0.31)		
h=9	−3.14***	0.09**	0.42***	−0.31***	1.72***	0.25	−174.01
	(0.40)	(0.04)	(0.07)	(0.07)	(0.30)		
h=10	−2.89***	0.09**	0.39***	−0.25***	1.43***	0.20	−184.47
	(0.38)	(0.04)	(0.07)	(0.06)	(0.30)		
h=11	−2.69***	0.09**	0.36***	−0.18***	1.16***	0.16	−193.58
	(0.37)	(0.04)	(0.06)	(0.06)	(0.30)		
h=12	−2.60***	0.09***	0.36***	−0.15***	0.85***	0.14	−197.88
	(0.37)	(0.04)	(0.06)	(0.06)	(0.31)		
h=13	−2.52***	0.10***	0.35***	−0.11**	0.63*	0.12	−201.63
	(0.37)	(0.04)	(0.06)	(0.06)	(0.32)		
h=14	−2.44***	0.10***	0.34***	−0.06	0.40	0.11	−204.77
	(0.38)	(0.04)	(0.06)	(0.06)	(0.33)		
h=15	−2.40***	0.11***	0.33***	−0.04	0.14	0.10	−207.13
	(0.38)	(0.04)	(0.06)	(0.06)	(0.34)		
h=16	−2.34***	0.11***	0.30***	−0.02	−0.13	0.08	−211.28
	(0.37)	(0.04)	(0.06)	(0.05)	(0.35)		
h=17	−2.28***	0.11***	0.28***	−0.02	−0.43	0.07	−213.88
	(0.37)	(0.04)	(0.06)	(0.05)	(0.37)		
h=18	−2.23***	0.11***	0.27***	−0.02	−0.78**	0.06	−214.88
	(0.37)	(0.04)	(0.06)	(0.05)	(0.39)		

Notes: This table presents augmented logit estimated coefficients. Consta refers to the constant term, b1 to the level component, b2 to the slope and b3 to the curvature component of the yield curve estimated. The dependent variable is a binary variable which accounts for 1 if there is a recession period and 0 otherwise. PsR2 refers to the pseudo R^2 estimate, while LogL is the log likelihood estimate under the restricted model. Finally h represents the forecasting periods which go from 1 until 18 months. The estimated standard errors are in parentheses. ***,**,* indicate significance at the 1, 5 and 10 % significance levels, respectively. The sample observations are in monthly terms and the period of the estimation runs from 1970:M1 until 2012:M12.

The significance values obtained are very similar to those of previous works applied to the US market. There is evidence of the predictive capacity or markets anticipation with respect to recessions. Also, we should reinforce the idea that we have computed these recession periods but always comparing them with the data made available for this same analysis period considered.

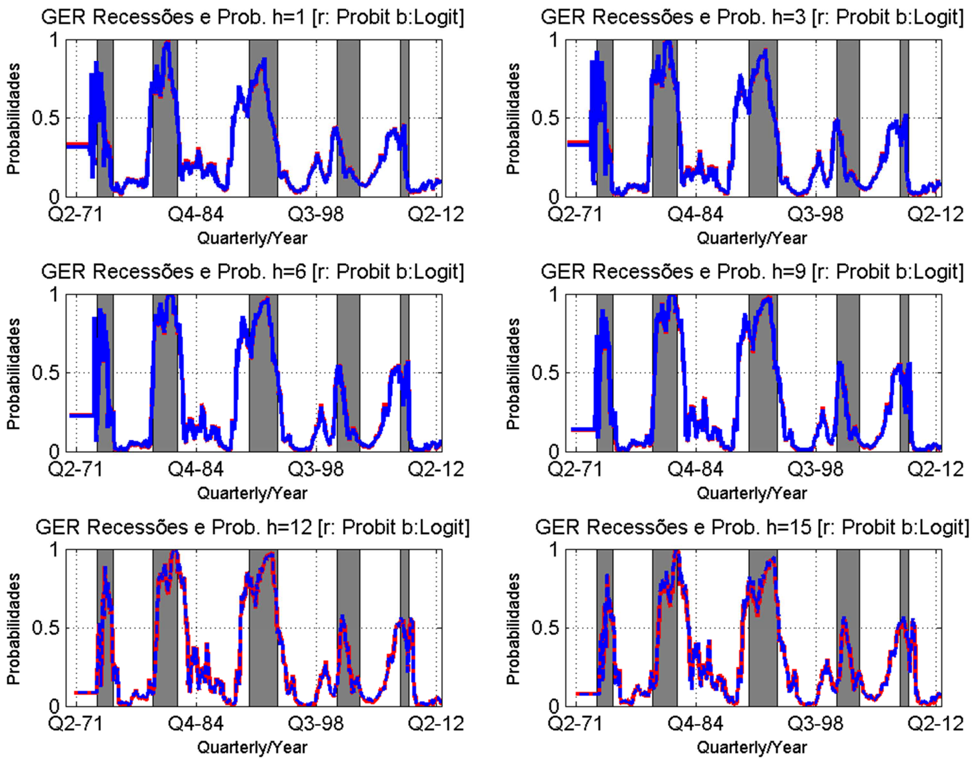
The logit results are very similar to those of probit. The results of one of the models only come to reinforce in terms of robustness check the capacity of the other. As such, and given that this has happened for all the countries under analysis we will skip the presentation of the logit results for the next two countries (Germany and Portugal) and we present only on tables 5 and 6 the results of the probit estimates for the simple and augmented models, respectively for Germany, while tables 7 and 8 present the estimates of the simple probit and augmented probit for the Portuguese case, respectively. Moreover, the last conclusion that the inclusion of the dependent lagged variable as an independent predictor improves a lot the results in terms of goodness of fit will still be demonstrated for these two additional countries. As such, and for all the countries under observation in recession periods, the pseudo R^2 increases a lot, thus increasing the model explanatory power, especially at the 1 month forecasting horizon, and so increases the persistence in the cycle phases. Also in general terms, when the autoregressive term is included, and independently of the country, the other explanatory variables keep their significance which reinforces our results. However, some in specific forecasting horizons lose their significance but not their explanatory power, turning them important to explain recessions in European countries, at least up to 13 months for all the yield curve components estimated.

To reinforce the fact that we will from now on discard the logit model results, we present in figure 2 the plot of the predictive power of both logit (the red line) and probit (the blue line) estimates for different forecasting horizons, namely of 1, 3, 6, 9, 12 and 15 months. Once again we need to observe that using one or the other model becomes indifferent. In these plots we have the probability of a recession filtered by the model, meaning the model adjustments to both logit and probit estimates.

Again, we can observe from this figure that the probability increases a lot before the recession periods and also during these same recession moments. Still, these plots confirm that the predictability degree is substantial because we have a good adjustment. So, we have presented the logit results for the UK case but this one only confirms the robustness of the results achieved through the probit model, meaning that we have no clear additional advantage in using the logit model, and as such we will not present its results when considering both Germany and Portugal estimates.

In table 5 the results of the simple probit estimates for the German country are presented. Even with a different country we see that all the components of the yield curve are necessary to explain recessions in this country at least for a forecasting horizon of one year, when all of them keep their significance. However, some interesting differences deserve to be mentioned in this case. First of all the curvature component is positive in Germany and significant for all the forecasting periods considered. The slope remains positive as well as the level, but now the level loses its significance from the 15^{th} forecasting month onwards. This means that in the German case as both the yield spread, the level and/or the curvature increases, also will the likelihood of recession.

Figure 2: Germany Recessions and Predictive Power of both probit and logit model estimates for forecasting horizons of 1, 3, 6, 9, 12 and 15 months



Moreover, the goodness of fit parameter increases is higher for the simple probit estimates in Germany than they were in the UK and it only starts to decrease from the 9^{th} forecasting month onwards. With this in mind we may conclude that different countries are influenced in different forms by the yield curve components being this influence always positive over recession in Germany but not in the UK. One possible explanation is that Germany is included in the Euro area, with its specific policies and not the UK. Still, we need to include in our sample a few more European Monetary Union countries into the analysis in order to take straight conclusions from here. Moreover, also the constant term loses its significance in the German probit estimates.

The robustness of our findings strengthens the claim that the yield curve should be considered a useful recession predictor in Europe. The yield curve components are in favor and serve as a recession indicator.

Besides, this predictability remains unchanged when the probit model is extended to include the autoregressive term as well as by using both the simple and the extended logit model to also include only the components and besides the components the autoregressive term.

Table 5: Simple Probit Estimates of the Probability of Recession – GER

	consta	b1	b2	b3	PsR2	LogL
h=1	−0.530**	0.091***	0.351***	0.088***	0.282	−230.112
	(0.25)	(0.03)	(0.04)	(0.02)		
h=2	−0.468*	0.092***	0.407***	0.088***	0.282	−217.377
	(0.25)	(0.03)	(0.04)	(0.02)		
h=3	−0.406	0.094***	0.446***	0.103***	0.318	−206.518
	(0.26)	(0.03)	(0.04)	(0.02)		
h=4	−0.361	0.097***	0.474***	0.120***	0.347	−197.497
	(0.27)	(0.03)	(0.05)	(0.02)		
h=5	−0.302	0.097***	0.494***	0.141***	0.371	−189.956
	(0.27)	(0.04)	(0.05)	(0.02)		
h=6	−0.237	0.098***	0.522***	0.161***	0.399	−181.347
	(0.28)	(0.04)	(0.05)	(0.02)		
h=7	−0.273	0.107***	0.510***	0.180***	0.406	−179.124
	(0.28)	(0.04)	(0.05)	(0.02)		
h=8	−0.29	0.11***	0.49***	0.20***	0.41	−178.28
	(0.28)	(0.04)	(0.05)	(0.03)		
h=9	−0.26	0.11***	0.50***	0.21***	0.42	−175.71
	(0.28)	(0.04)	(0.05)	(0.03)		
h=10	−0.23	0.11***	0.48***	0.22***	0.41	−176.43
	(0.29)	(0.04)	(0.05)	(0.03)		
h=11	−0.23	0.10***	0.45***	0.22***	0.40	−180.30
	(0.28)	(0.04)	(0.05)	(0.03)		
h=12	−0.22	0.10***	0.43***	0.22***	0.39	−183.58
	(0.28)	(0.04)	(0.04)	(0.03)		
h=13	−0.18	0.09**	0.40***	0.22***	0.37	−187.66
	(0.28)	(0.04)	(0.04)	(0.03)		
h=14	−0.15	0.08**	0.37***	0.22***	0.36	−192.58
	(0.28)	(0.04)	(0.04)	(0.03)		
h=15	−0.14	0.07*	0.34***	0.21***	0.33	−200.73
	(0.27)	(0.04)	(0.04)	(0.03)		
h=16	−0.14	0.06	0.31***	0.20***	0.30	−209.25
	(0.27)	(0.04)	(0.04)	(0.02)		
h=17	−0.12	0.05	0.29***	0.19***	0.27	−216.71
	(0.27)	(0.03)	(0.04)	(0.02)		
h=18	−0.11	0.04	0.26***	0.17***	0.24	−224.95
	(0.26)	(0.03)	(0.04)	(0.02)		

Notes: This table presents simple probit estimated coefficients. Consta refers to the constant term, b1 to the level component, b2 to the slope and b3 to the curvature component of the yield curve estimated. The dependent variable is a binary variable which accounts for 1 if there is a recession period and 0 otherwise. PsR2 refers to the pseudo R^2 estimate, while LogL is the log likelihood estimate under the restricted model. Finally h represents the forecasting periods which go from 1 until 18 months. The estimated standard errors are in parentheses. ***,**,* indicate significance at the 1, 5 and 10 % significance levels, respectively. The sample observations are in monthly terms and the period of the estimation runs from 1970:M1 until 2012:M12.

So, first it is readily observable from one up to thirteen months and gives a signal that is easy to interpret. Second, the expectations theory for the term structure of interest rates provides a theoretical foundation for the predictive power of the yield curve.

Table 6 presents the probit estimates for the German sample when it is included as regressor the autoregressive regression term. But the main conclusions with respect to those of table 5 remain practically unchanged. The only and huge difference respects to the goodness of fit making us state once again that including the autoregressive term leads to an increased significance of the results. Still we have a positive influence of the yield curve components over recessions forecasting, but in this situation the level coefficient loses some of its significance for short term forecasting horizons.

In sum, all the yield curve components have a positive sign implying that as the yield long term (level), short term (slope) and medium term (curvature) components increase (decrease) the likelihood of recessions also increase (decrease).

Table 6: Probit Estimates of the Probability of Regression [autoregressive Term] - GER

	consta	b1	b2	b3	b4	PsR2	LogL
h=1	−1.837***	0.043	0.420***	0.103*	4.340***	0.883	−35.628
	(0.52)	(0.07)	(0.11)	(0.05)	(0.43)		
h=2	−1.483***	0.038	0.527***	0.082**	3.736***	0.816	−55.673
	(0.43)	(0.06)	(0.10)	(0.04)	(0.34)		
h=3	−1.250***	0.049	0.527***	0.109***	3.176***	0.755	−74.105
	(0.38)	(0.05)	(0.09)	(0.04)	(0.28)		
h=4	−1.086***	0.057	0.508***	0.130***	2.710***	0.700	−90.594
	(0.35)	(0.05)	(0.08)	(0.03)	(0.24)		
h=5	−0.922***	0.061	0.481***	0.158***	2.330***	0.651	−105.253
	(0.33)	(0.04)	(0.07)	(0.03)	(0.21)		
h=6	−0.770**	0.064	0.488***	0.176***	2.020***	0.616	−115.873
	(0.32)	(0.04)	(0.06)	(0.03)	(0.20)		
h=7	−0.739**	0.075*	0.445***	0.194***	1.718***	0.570	−129.521
	(0.31)	(0.04)	(0.06)	(0.03)	(0.19)		
h=8	−0.67**	0.08*	0.41***	0.21***	1.47***	0.53	−141.20
	(0.31)	(0.04)	(0.05)	(0.03)	(0.18)		
h=9	−0.58*	0.08**	0.42***	0.21***	1.21***	0.50	−150.17
	(0.30)	(0.04)	(0.05)	(0.03)	(0.18)		
h=10	−0.47	0.08**	0.40***	0.23***	0.99***	0.47	−159.21
	(0.30)	(0.04)	(0.05)	(0.03)	(0.17)		
h=11	−0.43	0.08**	0.38***	0.22***	0.76***	0.43	−169.99
	(0.29)	(0.04)	(0.05)	(0.03)	(0.17)		
h=12	−0.36	0.08**	0.38***	0.22***	0.54***	0.40	−178.32
	(0.29)	(0.04)	(0.05)	(0.03)	(0.17)		
h=13	−0.28	0.08**	0.37***	0.22***	0.38**	0.38	−185.13
	(0.28)	(0.04)	(0.05)	(0.03)	(0.17)		
h=14	−0.21	0.07*	0.35***	0.22***	0.22	0.36	−191.75
	(0.28)	(0.04)	(0.05)	(0.03)	(0.17)		
h=15	−0.16	0.06*	0.33***	0.21***	0.07	0.33	−200.64
	(0.28)	(0.04)	(0.04)	(0.03)	(0.17)		
h=16	−0.12	0.06*	0.32***	0.20***	−0.06	0.30	−209.19
	(0.27)	(0.04)	(0.04)	(0.02)	(0.17)		
h=17	−0.06	0.05	0.31***	0.19***	−0.19	0.28	−216.05
	(0.27)	(0.04)	(0.04)	(0.02)	(0.17)		
h=18	−0.01	0.05	0.30***	0.18***	−0.31*	0.25	−223.19
	(0.27)	(0.04)	(0.04)	(0.02)	(0.17)		

Notes: This table presents augmented probit estimated coefficients. Consta refers to the constant term, b1 to the level component, b2 to the slope and b3 to the curvature component of the yield curve estimated. The dependent variable is a binary variable which accounts for 1 if there is a recession period and 0 otherwise. PsR2 refers to the pseudo R^2 estimate, while LogL is the log likelihood estimate under the restricted model. Finally h represents the forecasting periods which go from 1 until 18 months. The estimated standard errors are in parentheses. ***,**,* indicate significance at the 1, 5 and 10 % significance levels, respectively. The sample observations are in monthly terms and the period of the estimation runs from 1970:M1 until 2012:M12.

With respect to the Portuguese case tables 7 and 8 present the coefficient estimates obtained through the employment of the simple and augmented probit model, respectively. In this country while the curvature coefficient remains statistically significant and positive for all the forecasting horizons considered, both the level and the slope yield curve components estimated have a negative influence over the probability of recession’s occurrence. This negative sign implies that as the yield level and slope decrease, the likelihood of recession’s increase, which is in accordance to most of the previous literature studies applied to less developed markets, like Turkey, which consider the slope as a regressor.

Table 7: Simple Probit Estimates of the Probability of Recession – POR

	consta	b1	b2	b3	PsR2	LogL
h=1	−0.249	−0.070***	−0.116***	0.136***	0.226	−141.740
	(0.21)	(0.02)	(0.04)	(0.03)		
h=2	−0.132	−0.084***	−0.114***	0.148***	0.226	−138.454
	(0.22)	(0.02)	(0.04)	(0.03)		
h=3	0.160	−0.118***	−0.108***	0.187***	0.263	−130.660
	(0.24)	(0.03)	(0.04)	(0.03)		
h=4	0.348	−0.139***	−0.097**	0.213***	0.288	−126.112
	(0.25)	(0.03)	(0.04)	(0.04)		
h=5	0.429	−0.148***	−0.085*	0.218***	0.293	−125.001
	(0.26)	(0.03)	(0.04)	(0.04)		
h=6	0.455*	−0.150***	−0.095**	0.225***	0.294	−124.605
	(0.26)	(0.03)	(0.05)	(0.04)		
h=7	0.470*	−0.151***	−0.119**	0.237***	0.295	−124.270
	(0.26)	(0.03)	(0.05)	(0.04)		
h=8	0.50*	−0.15***	−0.13**	0.24***	0.29	−124.60
	(0.26)	(0.03)	(0.06)	(0.04)		
h=9	0.55**	−0.16***	−0.13**	0.25***	0.29	−124.76
	(0.27)	(0.03)	(0.06)	(0.04)		
h=10	0.53**	−0.15***	−0.14**	0.24***	0.28	−127.13
	(0.26)	(0.03)	(0.06)	(0.04)		
h=11	0.47*	−0.15***	−0.14**	0.23***	0.26	−130.22
	(0.25)	(0.03)	(0.06)	(0.04)		
h=12	0.47*	−0.14***	−0.15***	0.23***	0.25	−131.15
	(0.25)	(0.03)	(0.06)	(0.04)		
h=13	0.44*	−0.14***	−0.16***	0.23***	0.24	−133.00
	(0.25)	(0.03)	(0.06)	(0.04)		
h=14	0.42*	−0.14***	−0.17***	0.22***	0.23	−134.27
	(0.24)	(0.03)	(0.06)	(0.04)		
h=15	0.42*	−0.14***	−0.19***	0.23***	0.23	−134.75
	(0.24)	(0.03)	(0.06)	(0.04)		
h=16	0.43*	−0.14***	−0.20***	0.23***	0.22	−135.52
	(0.24)	(0.03)	(0.06)	(0.04)		
h=17	0.38	−0.13***	−0.21***	0.23***	0.21	−136.97
	(0.24)	(0.03)	(0.06)	(0.04)		
h=18	0.31	−0.12***	−0.22***	0.22***	0.20	−139.49
	(0.23)	(0.02)	(0.06)	(0.04)		

Notes: This table presents simple probit estimated coefficients. Consta refers to the constant term, b1 to the level component, b2 to the slope and b3 to the curvature component of the yield curve estimated. The dependent variable is a binary variable which accounts for 1 if there is a recession period and 0 otherwise. PsR2 refers to the pseudo R^2 estimate, while LogL is the log likelihood estimate under the restricted model. Finally h represents the forecasting periods which go from 1 until 18 months. The estimated standard errors are in parentheses. ***,**,* indicate significance at the 1, 5 and 10 % significance levels, respectively. The sample observations are in monthly terms and the period of the estimation runs from 1970:M1 until 2012:M12.

Curiously in Portugal and for all forecasting horizons, all the yield components have a statistically significant impact meaning that in this case all of them have predictive power on the recessions, also having very similar goodness of fit values for all these forecasting horizons considered. This fact is justified by the characteristics of the country under analysis because, despite being the less developed one when compared to the other two above analyzed, Portugal has been one of the recued countries in the European Union due to the recent financial crisis, which translated into profound reforms inside the country in order to beat the internal deficit.

When we include in the probit regressions the autoregressive term we continue to observe the same negative impact of the level and slope, and the positive impact of the curvature component. However, in the autoregressive term included there is a positive impact over the probability of recessions in Portugal but only up to the forecasting horizon of twelve months. Also, and similar to what we have obtained for the other countries in the sample the goodness of fit values increase when this additional term is included in the analysis, decreasing also as the forecasting horizon increases. However, the autoregressive term coefficient loses its significance for months 11 and 12 of forecasting horizon.

Table 8: Probit Estimates of the Probability of Regression [autoregressive Term] - POR

	consta	b1	b2	b3	b4	PsR2	LogL
h=1	−1.690***	−0.053	−0.087	0.082	3.628***	0.813	−33.736
	(0.40)	(0.04)	(0.09)	(0.06)	(0.33)		
h=2	−1.226***	−0.072**	−0.102	0.115**	2.935***	0.692	−55.005
	(0.33)	(0.03)	(0.07)	(0.05)	(0.27)		
h=3	−0.672**	−0.115***	−0.111	0.176***	2.492***	0.616	−68.086
	(0.31)	(0.04)	(0.07)	(0.05)	(0.25)		
h=4	−0.343	−0.137***	−0.112*	0.208***	2.162***	0.558	−78.197
	(0.31)	(0.04)	(0.07)	(0.05)	(0.24)		
h=5	−0.189	−0.139***	−0.109	0.208***	1.839***	0.495	−89.247
	(0.30)	(0.04)	(0.07)	(0.05)	(0.23)		
h=6	−0.078	−0.139***	−0.126*	0.216***	1.561***	0.442	−98.495
	(0.30)	(0.03)	(0.07)	(0.05)	(0.22)		
h=7	0.020	−0.139***	−0.145**	0.225***	1.293***	0.397	−106.358
	(0.29)	(0.03)	(0.07)	(0.05)	(0.22)		
h=8	0.14	−0.14***	−0.14**	0.23***	1.04***	0.36	−113.09
	(0.28)	(0.03)	(0.06)	(0.04)	(0.22)		
h=9	0.29	−0.15***	−0.14**	0.23***	0.78***	0.33	−118.28
	(0.28)	(0.03)	(0.06)	(0.04)	(0.22)		
h=10	0.34	−0.15***	−0.14**	0.23***	0.54**	0.29	−124.07
	(0.27)	(0.03)	(0.06)	(0.04)	(0.22)		
h=11	0.37	−0.14***	−0.14**	0.22***	0.30	0.26	−129.28
	(0.26)	(0.03)	(0.06)	(0.04)	(0.22)		
h=12	0.46*	−0.14***	−0.15***	0.23***	0.04	0.25	−131.14
	(0.26)	(0.03)	(0.06)	(0.04)	(0.22)		
h=13	0.51**	−0.14***	−0.16***	0.23***	−0.25	0.24	−132.42
	(0.26)	(0.03)	(0.06)	(0.04)	(0.24)		
h=14	0.59**	−0.15***	−0.18***	0.25***	−0.62**	0.25	−131.25
	(0.25)	(0.03)	(0.06)	(0.04)	(0.26)		
h=15	0.64**	−0.15***	−0.21***	0.26***	−0.82***	0.25	−130.05
	(0.25)	(0.03)	(0.06)	(0.04)	(0.28)		
h=16	0.64**	−0.15***	−0.22***	0.26***	−0.85***	0.25	−130.54
	(0.25)	(0.03)	(0.06)	(0.04)	(0.28)		
h=17	0.56**	−0.14***	−0.23***	0.25***	−0.71***	0.23	−133.26
	(0.25)	(0.03)	(0.06)	(0.04)	(0.27)		
h=18	0.45*	−0.13***	−0.23***	0.23***	−0.54**	0.21	−137.13
	(0.24)	(0.02)	(0.06)	(0.04)	(0.25)		

Notes: This table presents augmented probit estimated coefficients. Consta refers to the constant term, b1 to the level component, b2 to the slope and b3 to the curvature component of the yield curve estimated. The dependent variable is a binary variable which accounts for 1 if there is a recession period and 0 otherwise. PsR2 refers to the pseudo R^2 estimate, while LogL is the log likelihood estimate under the restricted model. Finally h represents the forecasting periods which go from 1 until 18 months. The estimated standard errors are in parentheses. ***,**,* indicate significance at the 1, 5 and 10 % significance levels, respectively. The sample observations are in monthly terms and the period of the estimation runs from 1970:M1 until 2012:M12.

So, for countries belonging to the monetary union it seems there are contradictory signs with respect to the yield curve components decomposition. The countries under analysis are very different in terms of characteristics, which may justify this fact. However, and overall we still have predictive power of all the three yield curve components and of the autoregressive term, no matter the fact if the country belongs to the monetary union or not. But signs with respect to the curvature change and we need to perform a deeper analysis including more countries under analysis, in order to be able to take some inference from the results attained here. In fact, this research is currently being performed for a much huge sample of countries belonging to both the monetary union or not. Also the fact that all recession period has been estimated through the available

data could be influencing the results and to discard this possibility we will also employ another methodology as presented above but not employed here in this current work.
For now we need to retain some basic information from all the analysis performed which is the fact that including the autoregressive term improves the goodness of fit of our model and that all the yield curve components have predictive power on the recessions despite the country under analysis.

5. Conclusions

This work examined the predictive power of the yield curve components over the probability of recessions for three different countries in Europe (UK, Germany and Portugal) considering monthly data for the period that goes from January 1970 until December 2012.
Unlike many of the previous literature, we take here a different approach, not analyzing the difference between short and long term interest rates (yield spread) but having into account the three factor models decomposition of the term structure of interest rates. As such, we start by estimating the components shape of the term structure of interest rates through the Diebold and Li model. Given that all the countries under analysis have different specificities and not all of them see recessions entering into their economies at the same time and given that there could be different individual recession periods for this heterogeneous sample, we do not resort to the dating providing by official authorities but we do an individual dating for each of the countries by applying the algorithm BBQ to estimate expansion and recession periods. After we join this two-step estimation procedure using the probabilistic models logit and probit to estimate the coefficients and the adjustment curves between both considering only the components as regressor, and also by estimating the models through their augmented version which corresponds to include the autoregressive term of the dependent variable.
Results attained seem to indicate that both slope and level components have a positive and significant influence over the entire period of forecasting horizons considered (up to 18 months) in the UK. The curvature negative sign for the UK indicates that when it decreases the likelihood of recession increases, although this same component revealed to have a positive influence in Germany and Portugal. In the German case all yield curve components have a positive influence over the likelihood of recessions while for Portugal both the level and the slope have a negative influence. In the Portuguese case we may be tempted to state that by considering the recent financial crisis, which was originated in the advanced economies, but has hit many countries including Portugal and pushed them into a recession, that the inverted yield curve (negative slope) can be regarded as an indicator of made in Portugal recession.
Moreover, the goodness of fit measure improves when the autoregressive term is included for all countries under analysis, while the logit model estimates only confirm the validity of the probit model used, given that the main conclusions remain unchanged. Still, this goodness of fit decreases while the forecasting horizon increases, turning evident that the predictive power of the yield curve seems to be declining over time as other authors results confirm..

A lot more remains to be done and is currently being developed. This work is only a sample of a much higher existent work. Future research includes the application to other European countries (currently being developed) as well as the inclusion of other macroeconomic aggregates to see if results improve in terms of recession prediction through the yield curve components.

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