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Yield spread as a leading indicator of Tunisian industrial production

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Abstract- *Can the yield spread, which has been found to predict with surprising accuracy the movement of key macroeconomic variables of developed countries, also predict such variables for an emerging country. This paper is an attempt to answer empirically this question for the Tunisian economy. It also examines international financial linkages and how the euro area yield curve helps to predict domestic macro financial variables. Although the phenomenon has been widely examined in developed market economies, similar studies are virtually absent in the case of emerging economies. In part, this is because in developing economies with administrated interest rates, the yield curve has been either completely absent or not market determined and thus did not form a suitable test case. In the Tunisian financial market, there has been considerable improvement in terms of volumes, variety of instruments, numbers of participants and dissemination of information, and a yield curve particularly in case of government securities started emerging since 2000.*

In our study, two approaches are implemented. The first one, widely used, consists in regressing the growth rate of the coincident indicator on the leading indicator. In the second one, we examine the usefulness of the yield spread in predicting whether or not the economy will be in recession in the future. So, in that particular case we use a Probit model. For both approaches we use the in-sample forecasting ability as well as the out-of-sample accuracy of the outcomes.

The results are somewhat tentative but consistent with the similar studies conducted in case of other countries. Findings of the study provide evidence that the yield curve could be considered as a leading indicator of real growth or recessions in Tunisian context, and consequently may be useful for both to private investors and to policy makes for forecasting purposes and, perhaps more importantly to understand the ongoing process of international financial integration.

Key words- *yield spread; in-sample forecasting; out-of-sample forecasting; economic growth; recessions; leading indicator; predictive content; linear regression; probit model.*

1. Introduction

There is a significant amount of empirical evidence to suggest that the asset prices are forwardlooking and, consequently, constitute a class of potentially useful predictor of macroeconomic variables[1]. The literature on forecasting using asset prices has identified in particular the yield spread. It's the difference between long-term and short-term interest rates. While there has been evidence of association between yield spreads and real economic activity in every case of developed economies, predictability varies across the countries. It has been suggested that country-wise variations in the predictive power is on account of the differences in regulatory regimes among the economies. Although the phenomenon has been widely examined in developed economies, similar studies are virtually absent in the case of emerging economies. In part, this is because in developing economies with administrated interest rates, the yield curve has been either completely absent or not market determined and thus did not form a suitable test case.

After having granted the necessity of a financial deepening, development of domestic debt security markets in these economies in the very recent years reflects their efforts to self-insure against 'sudden stops' and reversals in international capital flows following the string of crises of the 1990s (IMF 2006). From a macroeconomic perspective indeed, domestic debt markets were seen by policy makers in emerging countries as an alternative source of financing to cushion against lost access to external funding. Moreover, from a microeconomic perspective, deeper domestic debt markets were expected to help widen the menu of instruments available to address currency and maturity mismatches, which reduces risks of financial crises. For all these reasons, local authorities have engaged in deliberate efforts to develop domestic debt markets. Until 1986, the Tunisian financial system was characterised by a highly regulated regime, which has

[1] For a recent review of the extensive literature on the historical and international performance of asset prices as leading indicators, see for example Stock and Watson (2003b): they provided a survey of 66 previous papers on this subject.

since been gradually liberalized. By the mid-1990s, there has been considerable improvement in terms of volumes, variety of instruments, number of participants and dissemination of information, and a yield curve particularly in case of government securities started emerging since 2000.

The present paper is an attempt to test the relationship between the yield spreads and real economic activity in Tunisian context. It is organized as follows: section I explains the economic rationale behind observed association between the yield spread and real economic activity. Section II presents a survey of the literature on the phenomenon under study. Section III sets out the empirical results of our exercise conducted on the Tunisian economy when we evaluate the explanatory power of several different combinations of yield spreads, based on the long rates of five and ten years, and the short rates of one year, three months and one month, in their ability to explain cumulative growth of real industrial production. We compare also the explanatory power of the domestic spreads with the one of foreign spread. Section V concludes this study.

2. Yield spread as predictor of real economic activity: theoretical rationale

According to Peel and Taylor (1998), it is a "stylised fact" that the slope of the yield curve can be used as a leading indicator of future economic activity. Therefore, this section will not devote much time to reviewing the relevant theoretical reasons that explain the observed relationship between the yield spread and real economic activity. There are at least three main reasons that explain the relationship between the slope of the yield curve and real economic growth and thus explain why the yield curve might contain information about future growth or recessions. In general, this relationship is positive and, essentially, reflects the expectations of financial market participants regarding future economic growth. A positive spread between long-term and short-term interest rates (a steepening of the yield curve) is associated with an increase in real economy activity, while a negative spread (a flattening of the yield curve) is associated with a decline in real activity.

The first reason stems from the expectations hypothesis of the term structure of interest rates. This hypothesis states that long-term interest rates reflect the expected path of future short-term interest rates. In particular, it claims that, for any choice of holding period, investors do not expect to realise different returns from holding bonds of different maturity dates. The long-term rates can be considered a weighted average of expected future short-term rates. An anticipation of a recession implies an expectation of decline of future interest rates that is translated in a decrease of long-term interest rates. These expected reductions in interest rates may stem from countercyclical monetary policy designed to stimulate the economy[2]. In addition, they may reflect low rate of returns during recessions, explainable, among other factors, by credit market conditions[3] and by lower expectation of inflation. Indeed, the slope of the yield curve is calculated on nominal interest rates[4] and therefore embodies a term representing expected inflation. Since recessions are generally associated with low inflation rates, assuming for example that a downward Phillips-curve relationship holds, this can play a role in explaining the expectation of low rate of returns during recessions. Alternatively, if market participants anticipate an economic boom and future higher rates of return to investment, then expected future short rates exceed the current short rate, and the yield on long-term bonds should rise relative to short-term yields according to the expectations hypothesis.

Another reason which explains the above relationship is related to the effects of monetary policy. For example, when monetary policy is tightened, short-term interest rates rise; long-term rates also typically rise but usually by less than the current short rate, leading to a downwardsloping term structure. The monetary contraction can eventually reduce spending in sensitive sectors of the economy, causing economic growth to slow and, thus, the probability of a recession to increase. Estrella and Mishkin (1997) show that the monetary policy is an important determinant of term structure spread[5]. In particular, they observe that the credibility of the central bank affects the extent of the flattening of the yield curve in response to an increase in the central bank rate.

The third reason is given by Harvey (1988) and Hu (1993) and it is based on the maximisation of the intertemporal consumer choices. The central assumption is that consumers prefer a stable level of income rather than very

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[2] Haubrich and Dombrosky (1996) call this the « policy anticipations hypotheses ».

[3] The authors show also that the monetary policy is not the only determinant of the term structure spread. In fact, there is a significant predictive power for both real activity and inflation. They demonstrate by an empirical analysis that the yield curve has significant predictive power for real activity and inflation in both the United States and Europe. See Estrella and Mishkin (1997) for further details. Estrella (1997) presents also a theoretical rational expectations model that shows how the monetary policy is likely to be a key determinant of the relationship between the term structure of interest rates and future real output and inflation.

[4] Although the theoretical linkage expressed in economic models is between the real term structure and future economic activity, it's the relationship of the nominal term structure with economic activity that has been engaged the attention of empirical researchers for the simple reason that nominal term structure is so readily observable whereas the computation of the real term structure requires the estimation of inflation expectations of market participants. These expectations are not directly observable. In this case, Plosser and Rouwenhorst (1994) pointed out that one would expect the nominal term structure to forecast real activity better if the term structure of expected inflation is flat and stable over time rather than sloped and variable.

[5] But as Dueker (1997) explains, this is depends on their assessment of the size and duration of the recession's effect on short-term interest rates.

high income during expansion and very low income during slowdowns. In a simple model where the default-free bond is the only financial security available, if the consumers expect a reduction of their income - a recession - they prefer to save and buy long-term bonds in order to get payoffs in the slowdown. By doing that they increase the demand for long-term bond and that leads to a decrease of the corresponding yield. Further, to finance the purchase of the long-term bonds, a consumer may sell short-term bonds whose yields will increase. As a result, when a recession is expected, the yields curve flattens or inverts.

3. Survey of literature

Fama, as early as in 1986 and later Stambaugh in 1988 mentioned that term structure appears to predict real economic activity though these were not supported by any detailed statistical analysis[6]. The presented graphs show that rise and fall in forward rates precedes economic upswing and recession respectively. Since then a significant amount of empirical evidence has been conducted to test the existence of relationship between yield spread and real economic activity. The literature on term spreads uses different measures of yield spread[7]. The adage that an inverted yield curve signals a recession was formalized empirically, by a number of researchers in the late 1980s, including Laurent (1988, 1989), Campbell Harvey (1988, 1989), Stock and Watson (1989), Chen (1991), and Estrella and Hardouvelis (1991). These studies mainly focused on using the term spread to predict output growth (or in the case of Harvey 1988, consumption growth) using U.S. data. Of these studies, Estrella and Hardouvelis (1991) provided the most comprehensive documentation of the strong (in-sample) predictive content of the spread for output, including its ability to predict a binary recession indicator in probit regressions. This early work focused on bivariate relations, with the exception of Stock and Watson (1989), who used in-sample statistics for bivariate and multivariate regressions to identify the term spread and a default spread. Notably, when placed within a multivariate model, the predictive content of the term spread can change if monetary policy changes or the composition of economic shocks changes (Smets and Tsatsaronis 1997). Movements in expected future interest rates might not account for all the predictive power of the term spread. For example, Hamilton and Kim (2002) suggested that the term premium has important predictive content for output as well.

For the studies which forecast recessions rather than a quantitative measure of real output growth, Estrella and Hardouvelis (1991) and Estrella and Mishkin (1998) documented that the yield curve slope significantly outperforms other indicators in predicting recessions, particularly with horizon beyond one quarter. This forecast is done estimating a probit model. Dueker (1997) confirms this result using a modified probit model which includes a lagged dependent variable. Built on these works, many papers, on the one hand, give empirical results on the fact that these evidences are present also in the major countries of the European Union and, on the other hand, they try to improve or change the model used to forecast recessions. These papers include Bernard and Gerlach (1998), which provide a cross-country evidence on the usefulness of the term spreads in predicting the probability of recessions within eight quarters ahead. Estrella and Mishkin (1997) focus on a sample of major European economies (France, Germany, Italy and the United Kingdom). Sédillot (2001) provides an empirical evidence for France, Germany and the U. S. Ahrens (2002) evaluates the informational content of the term structure as a predictor of recession in eight OECD countries. Stock and Watson (2003b) examine the behaviour of various leading indicators before and during the U.S. recession that began in March 2001. Harvey (1991), Hu (1993), Davis and Henry (1994), Plosser and Rouwenhorst (1994), Bonser-Neal and Morley (1997), Kozicki (1997), Campbell (1999), Estrella and Mishkin (1997), and Estrella, Rodrigues, and Schich (2003), Moneta (2003), and Mehl (2006) generally conclude that the term spread has predictive content for real output growth in major OECD economies. Estrella, Rodrigues, and Schich (2003) use in-sample break tests to assess coefficient stability of the forecasting relations and typically fail to reject the null hypothesis of stability in the cases in which the term spread has the greatest estimated predictive content (mainly long horizon regressions). Additionally, Bernard and Gerlach (1998) and Estrella, Rodrigues, and Schich (2003) provide cross-country evidence on term spreads as predictors of a binary recession indicator for seven OECD countries. Unlike most of these papers, Plosser and Rouwenhorst (1994) considered multiple regressions that include the level and change of interest rates and concluded that, given the spread, the short rate has little predictive content for output in almost all the economies they consider.

These studies typically used in-sample statistics and data sets that start in 1970 or later. Three exceptions to this generally sanguine view are Davis and Fagan (1997), Smets and Tsatsaronis (1997) and Stock and Watson (2003a). Using a pseudo out-of-sample forecasting design,

[6] According to A. Estrella (2005), the analysis of the behaviour of interest rates of different maturities over the business cycle back at least to Mitchell (1913), Kesel (1965) and Butler (1978).

[7] Research on the United States business cycle has relied mostly on interest rates for U.S Treasury securities. One reason is convenience: data for maturities are available continuously for a long period. Another reason is that the pricing of these securities is not subject to significant credit risk premiums that, at least in principle, may change with maturity and over time. For similar reasons, studies of other countries tend to use data on national government debt securities. Rates on coupon bonds and notes are most easily accessible, but researchers in many countries have also produced zero-coupon rates, witch may directly matched with the timing of forecasts. Some analysts have also used, at short-term rates, the leading rates of the central bank or others rates of many market.

Davis and Fagan (1997) find evidence of sub-sample instability and report disappointing pseudo out-ofsample forecasting performance across nine EU economies. Smets and Tsatsaronis (1997) find instability in the yield curve–output relation in the 1990s in the United States and Germany.

Our paper follows the path of these studies with the aim of examining the forecasting ability of the yield spread in predicting growth and recession in the Tunisian context. The main object of our contribution is to carry out this investigation at different segments of the yield curve and testing therefore which specific spread is the best predictor of industrial production in the Tunisian economy.

4. Data description

Yield data used for the study were derived from the series of annualised yields of different maturity Treasury bonds and money-market interest rates compiled at daily intervals by the Central bank of Tunisia. The sample period is from month 1, 2001 to month 9, 2006. From the daily yield series, a series of month-end yields were extracted and these month-end yields were averaged to drive a series of monthly yields. The term spreads were computed from monthly yield series. The purpose of transformation the yield data to monthly series is to match the frequency of Industrial production data which are available at monthly intervals. In this article, the term spread[8] at time t, St, is the observed difference between a selected long term-yield YL_t and a selected short-term yield SYt : $St = LY_t - SY_t$. We consider the following list of spreads[9] :

- $S_1 = LY_1 - SY_1$ where : LY_1 is the annualised yield of ten year and SY_1 is the annualised yield of one year;
- $S_2 = LY_2 - SY_2$ where : LY_2 is the annualised yield of five year and SY_2 is the annualised yield of one month;
- $S_3 = LY_3 - SY_3$ where : LY_3 is the annualised yield of ten year and SY_3 is the annualised yield of one month;
- $S_4 = LY_4 - SY_4$ where : LY_4 is the annualised yield of ten year and SY_4 is the annualised yield of five year;
- $S_F = LY_F - SY_F$ where: LY_F is the annualised yield of five year and SY_F is the annualised yield of three month.

5. Methodology

The basic methodology used for testing forecasting power is the linear regression model and the probit model. For the linear model, measures of economic growth (Index of Industrial Production, IIP) are regressed on the spread and it takes the following form:

$$G_{t,t+k} = \alpha + \beta . S_t + \varepsilon_t$$

Where $G_{t,t+k}$ is the annualised percentage continuously compounded growth of IIP over k months, and it's defined as $G_{t,t+k} = [(1200/k) \times (\log IIP_{t+k} - \log IIP_t]$. IIP_{t+k} denotes the level of IIP during the month $t + k$ and IIP_t denotes the level of IIP during the month t.

Regressions are carried out to test the explanatory power of the yield spread in respect of industrial production growth over a k months ahead. Our approach to evaluate the explanatory power of the models is to use all available observations for estimating the regression model and to examine the statistical significance of the regression coefficients and the within sample explanatory power of the models considered[10].

For the second type of regression[11], we use a probit model in which the variable being predicted is a dummy variable R_t where $R_t=1$ if the economy is in recession in period t and $R_t = 0$ otherwise. The probability of recession at time

[8] Observe that the difference $YL_t - YS_t$ is proportional to the difference between the forward rate calculated from YLt et YSt , f_t , and YSt. The forward rate is defined as in Shiller, Campbell and Schoenholtz (1983):

$$f_t = \frac{[D_L YL_t - D_s YS_t]}{(D_L - D_s)}$$, where DL is the duration of the bond with L as maturity and DS is the duration of the bond with S as maturity. The difference $f_t - YS_t$ is the correct measure of the slope of the yield curve, but it is proportional to

$$LY_t - SY_t : f_t - SY_t = [D_L / (D_L - D_s)] \times (LY_t - SY_t).$$

[9] Since we subject our data to linear regression analysis we need to carry out tests for stationarity because it has been well established that non-stationarity data can produce spurious results. These tests are carried by means of augmented Dickey-Fuller tests. The results indicates that all spreads are integrated of order zero and there is no reason to be concerned about the danger of obtaining spurious results on account of non-stationarity in the regression analysis to follow.

[10] An econometric problem that arises whenever the cumulative growth of several months is forecasted in a time series regression of this nature where the overlap of observations is created is the autocorrelation of the regression error terms. When the cumulative growth of k months is forecasted, the regression errors tend to follow a moving average process of k-1. This results in inconsistent estimates of the standard errors of the regression coefficients. A well-known solution for this problem is to correct the variance-covariance matrix for serial correlation up to order k-1 adopting the Newey and West (1987) method. We have followed this procedure in all our regressions involving insample forecasting estimates.

[11] These two types of models may be compared in two dimensions: accuracy and robustness. But there is evidence that the most accurate binary models perform about as well as the linear regression (Estrella 2005).

t, with a forecast horizon of k periods is given by the following equation:

$$\Pr(R_t = 1) = \phi(c_0 + c_1 X_{t-k})$$

Where $\phi(.)$ is the cumulative standard density function, and X is the set of explanatory variables used to forecast the recessions.

6. Results and interpretations

6.1. The linear regression estimates

In measuring the term spread, the long term yield can be selected from several alternative long term maturity yields and likewise the short term yield can be chosen from several alternative short yields available to us in the data set. As forecasting tools, how do these different yield spreads perform? Is there an optimal choice of spread that would perform best for a particular forecasting horizon and for a particular beginning point in the period of activity forecasted? To answer these questions we examine the predictive power based on several alternative measures of yield spreads. Thus, Equation (1) is estimated for each spread over the 2001: M1 – 2006: M9 time period and the results of estimates are presented in tables 1, 2, 3, 4 and 5 in appendix.

We first examine the question of whether the choice between the yields of one and three months matters in the computation of the spread by comparing, in charts 1, the explanatory powers of the following regressions:

$$G_{t,t+k} = \alpha + \beta \times S_1 + \varepsilon_t$$
$$G_{t,t+k} = \alpha + \beta \times S_3 + \varepsilon_t$$

The $\overline{R}^2$ from the regression equation measures the proportion of the variation in real industrial production growth that is explained by the yield spread. At shorter horizons ($k \leq 4$months ahead) the one year yield does as better as the one month yield since their R-bar squares for these months are nearly the same. Given the shorter yield we now examine which of the longer yields are more effective by selecting in turn the five year and the ten year for computing the yield spread:

$$G_{t,t+k} = \alpha + \beta \times S_2 + \varepsilon_t$$
$$G_{t,t+k} = \alpha + \beta \times S_3 + \varepsilon_t$$

In the same way, we compare the predictive powers of the two equations (system 4) for horizons which exceed 6 months ahead. By comparing the explanatory powers (Charts 1), the spread S3 is more effective than the S2. The pattern in explanatory power suggests that explanatory power improves when the maturity period of the long term bond corresponds more closely with the forecasting horizon.

Financial markets have become increasingly integrated internationally and the nature of this integration and the transmission channels are not always well understood. A growing strand of literature has attempted to analyse international financial spillovers[12] but has largely ignored the slope of the yield curve**.** To this level the yield curve in the euro area can be expected to have some predictive content for growth in Tunisian economy. It can further be expected to convey better information on the future impact of common shocks, given that euro area debt security markets are more liquid than emerging economy ones. Last, the euro has an important role in the exchange rate policy of our economy. This magnifies the pass-through from euro area policy interest rates to our domestic interest rates. In turn, this contributes to potential co-movements between the slope of the yield curve in the euro area and the Tunisian domestic slope of the yield curve. And indeed, recent evidence from Frankel et al. (2004) and Shambaugh (2004) suggest that countries that have a pegged exchange rate follow base country interest rates more than countries that have a float, in particular when they have lifted capital controls. In other words, having fixed exchange rates forces countries to follow the monetary policy of the base country.

Against this background, we investigate the usefulness of the French slope of the yield curve as a predictor of domestic growth over k months ahead. To compare the explanatory power of foreign spread and domestic spread and test for the existence of international financial linkages[13], we estimate the following system of equation:

$$G_{t,t+k} = \alpha + \beta \times S_F + \varepsilon_t$$
$$G_{t,t+k} = \alpha + \beta \times S_3 + \varepsilon_t$$

[12] For example, Plosser and Rouwenhorst (1994), using time series techniques, find evidence that the US slope of the yield curve helps predict growth in both Germany and the U.K. (and vice versa) significantly. Bernard and Gerlach (1998), using probit estimation, find that the slope of the yield curve in the US and Germany helps predict recessions in other G7 countries, the UK and Japan, in particular, significantly. Those earlier contributions have two main features, however. First, they have ignored inflation altogether. Second, and more importantly, they have focused on a small number of industrial economies. Yet, when it comes to the slope of the yield curve, international financial linkages are also pronounced for emerging economies. Their small economic size makes the US or the euro area a possible determinant of their domestic inflation and growth.

[13] This predictive content may stem from (i) the larger economic size of the French comparatively to Tunisian one, which makes it an important component of foreign demand; (ii) the deeper French debt security market, which leads to a greater ability of its yield curve to convey information on the future impact of common shocks; and (iii) the prominent role played by the EURO in the exchange rate policy of domestic economy, which magnifies interest rate pass-through.

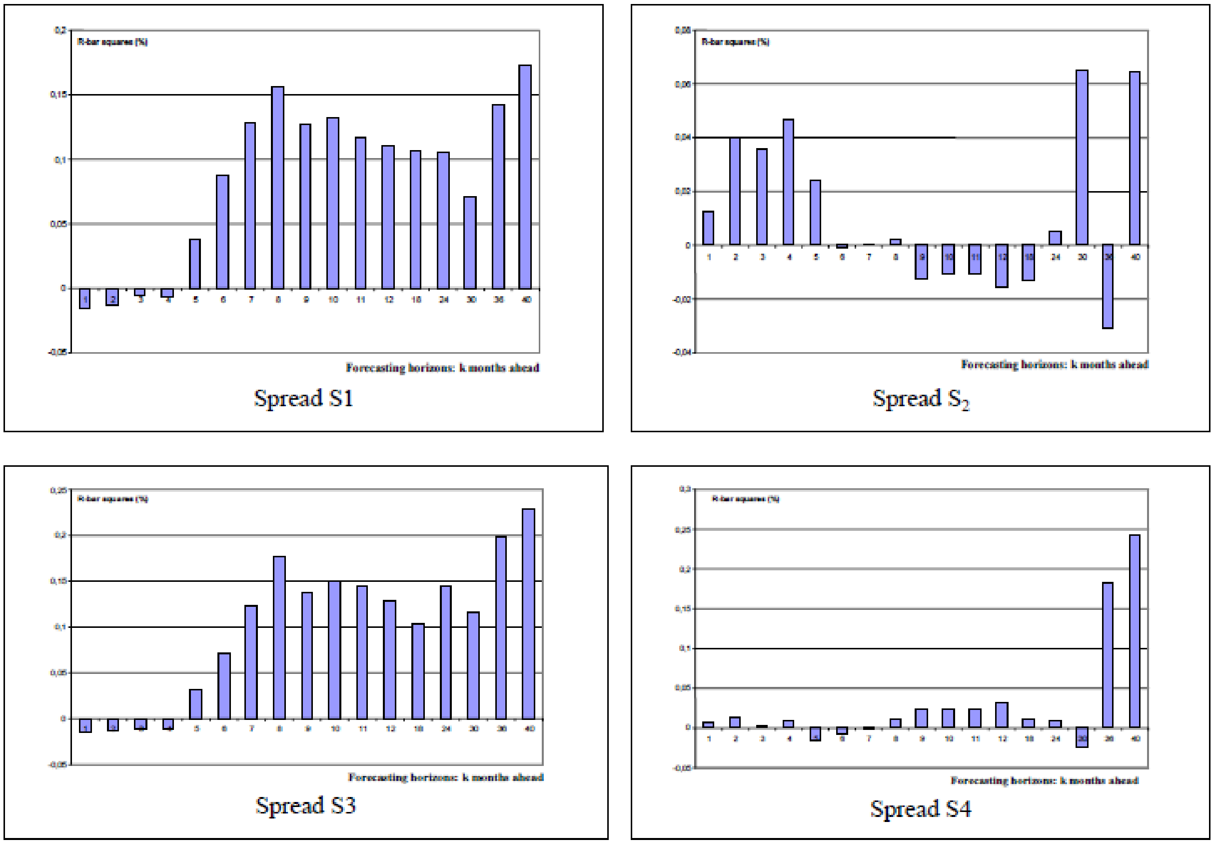


Chart 1: Explanatory power of the national spread (respectively S1, S2, S3 and S4) for real industrial

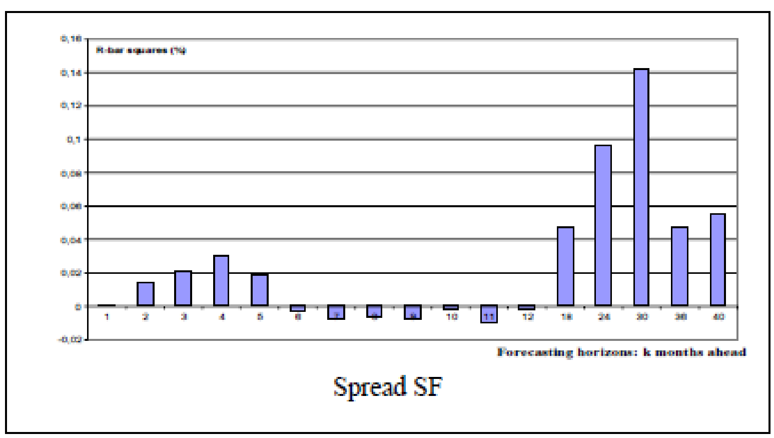


Chart 2: Explanatory power of the foreign spread (SF) for the real industrial production

The explanatory powers relative to the first equation of this system are always higher than ones relative to the second equation. By considering all spreads, the French one has in-sample forecasting an important information content for future k months ahead (k=18, 24, 30, 36 and 40) and, relatively to the international sector, it can be considered as a good leading indicator for Tunisian activity. In order to judge the overall performance of the forecasting equation, Charts 1 and 2 plot the R-bar squares values from estimating the forecasting equation 1 using the industrial production growth as the measure of the change in real economic activity. The $\overline{R}^2_{Si}(i=1,2,3,4,F)$ from the estimation of equation 1 range from -1.54 to 17.3

percent for i = 1, from -3.1 to 6.5 percent for i = 2 , from -5.54 to 30 percent for i = 3 , from -3.5 to 24 percent for i = 4 and from -1 to 14 percent for i = F. Thus the explanatory power d epends on yield spread considered and in general it increases with the lengthening of the forecast horizon. For the spread S_3 , for example, the proportion of variation in future real activity explained by this leading indicator is beyond 15% for forecasting horizon exceeds seven months, but less than 5% for very short-term forecasting horizon. This note is valid for the remaining spreads but the best leading indicators, following $\overline{R}^2$, are S_1 and S_3.

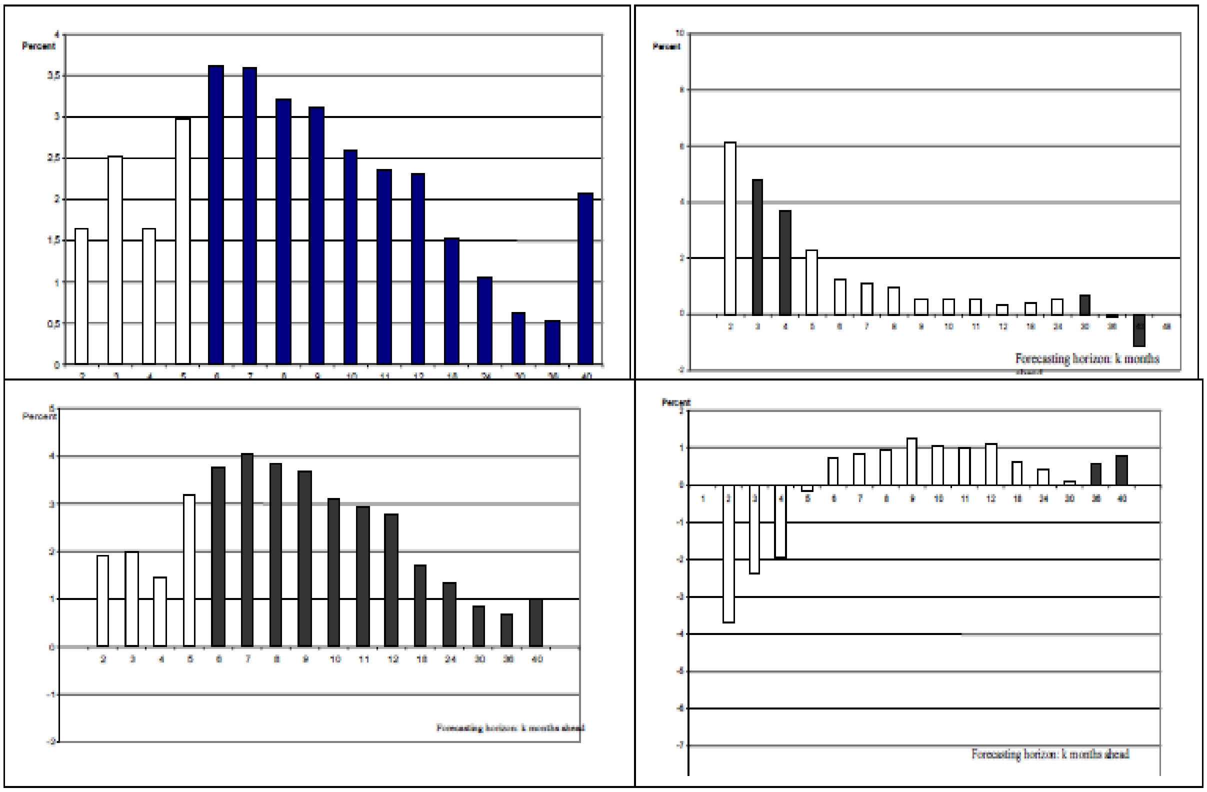


Chart 3: Change in the future real industrial production growth following a one-percentage-point change in the national spread (respectively S1, S2, S3 and S4)[14]

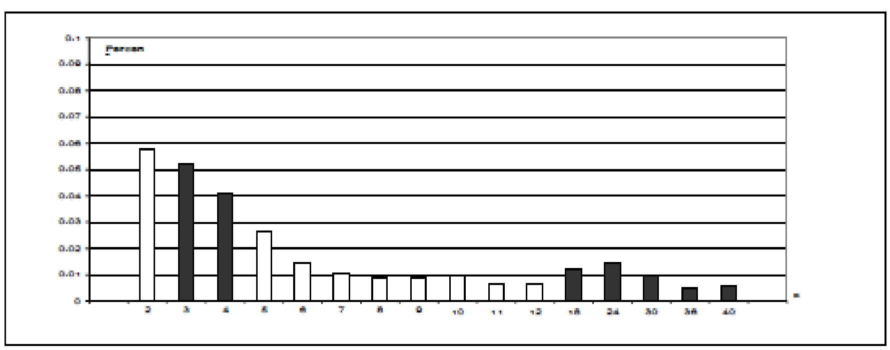


Chart 4: Change in the future real industrial production growth following a one-percentage-point change in the foreign spread (SF)

While the $\overline{R}^2$ provides an indicator of the explanatory power of the spreads for real IP growth, the coefficient β from equation 1 measures how much real IP growth changes following a onepercentage point change in the yield spread. A positive β would imply a positive relationship between the current yield curve and future economic growth. That is, the larger the spread is between long-term and short-term interest rates, the stronger real growth will be in the future. The yield spreads are found to have information content for future industrial production growth. Moreover, the response of industrial production growth is often positive, in line with expectations (i.e. a steepening of the yield curve is associated with higher expected growth). This is not always the case, however, as suggested by the results for the spread S4 and in some instances, estimated coefficients are unstable, switching sign across forecast horizons.

Charts 3 and 4 provide estimates of α_1 for the k months ahead forecasts for each spread. The coefficient β is positive in all estimation with the exception of that relative to S4 (for very short forecasting horizon). The statistical significance of β is indicated by a solid bar. For the spread S2, the solid bar also show that this leading indicator is a significant predictor of real economic growth in 75% observations related to forecasting horizon ranges. The charts 3 and 4 show that the numbers of observations for witch the yield spreads are statistically significant predictor of future industrial production growth increase with the forecast horizon. In particular, the spreads S2 and S3 are being significant since k = 6 and remain until k = 40.

Estimates of the β's themselves from the equation 1 provide an indication of the economic significance of the yield curve as a predictor of future real economic growth. In particular, the coefficient β measures the change in industrial production growth for a given one-percentage point change in the yield spread.

For the yield spread S3, for example, the chart 8 chows that a one-percentage-point increase in yield spread today is associated with an annualized 3.74-percentage-point increase in growth over the next six months, an annualized 4-percentage-point increase in growth over the seven months, an annualized 3.85-percentage-point increase in growth over the next eight months, an annualized 3.65-percentage-point increase in growth over the next nine months and an annualized 3.11-percentage-point increase in growth over the next ten months. Hence a widening of the yield spread would imply an increase in industrial production growth. For example, if real economic growth in the Tunisian industrial production was 3 percent, a widening of S_3 by one percent point would imply an increase in industrial production to 6 percent (2 + 1×4, 02) over the next seven months.

Together the results indicate that while the yield spread does help explain future real IP growth for many spreads, the strength of the predictive power varies by explanatory variable. The explanatory power of the yield spread is highest in the case of S1 and S3 and lowest for others spreads (Each bar represents the beta coefficients from the regression of future real industrial production growth on the corresponding yield spread. Statistical significance is indicated by a shaded bar. Source: see appendix and author's calculations).

6.2. The probit model estimates

A somewhat different approach involves the prediction of whether or not the economy will be in a recession K months ahead. This type of exercise abstracts from the actual magnitude of economic activity by focusing on the simple binary indicator variable. Although this forecast is in some sense less precise, the requirements on predictive power are in another sense less demanding and may increase the potential accuracy of the more limited forecast. Empirically, we would like to construct a model that translates the steepness of the yield curve at the present time into a likelihood of a recession some time in the future. Thus, we need to identify three components: a measure of steepness, a definition of recession, and a model that connects the two.

The approach we employ is a probit model equation, which uses the normal distribution to convert the value of a measure of yield spread steepness into a probability of recession k months ahead. Following Estrella and Hardouvelis (1991) and Estrella and Mishkin (1998), we study the ability of the slope of the yield curve to predict recessions in the Tunisian context. First, we estimate a probit model to obtain a probability of recession in the Tunisian economy between 1 and 7 months ahead. Then, we improve the probit model using the modification proposed by Dueker (1997). In order to analyse the predictive informative content in different segments of the yield curve we use five yield curve spreads as explanatory variables. We plug, therefore, in the right side of the equation (2) all the spreads listed in the first panel of Table 1 and we estimate the model[14].

Defining what is a recession is fundamental for constructing the binary time series *t R*. The National Bureau of Economic Research (NBER) officially dates the beginnings and ends of US recessions and it defines a recession as “a significant decline in activity spread across the economy, lasting more than a few months, visible in industrial production, employment, real income and wholesale ret ail trade”.

[14] The model is estimated using a non-linear method (the Newton-Raphson).

Table 1. Measures of fit for recession predictions (estimation period 2001M1-2006M9

Standard probit model : $\Pr(R_t = 1) = \phi(c_0 + c_1 X_{t-k})$

Predictor X_t	FORECAST HORIZON (Months)						
Spread S1	K=1	K=2	K=3	K=4	K=5	K=6	K=7
Pseudo-R^2	0,0188	0,0597	0,0671	0,0757	0,0982	0,1225	0,1421
McFadden R^2	0,0109	0,0064	0,0058	0,0062	0,019	0,0340	0,0051
T-stat	-1.0298	-0.7830	-0.7494	-0.7550	-1.2593	-1.6357	-0.5131
Spread S2	K=1	K=2	K=3	K=4	K=5	K=6	K=7
Pseudo-R^2	0,0268	0,0534	0,1029	0,0709	0,0861	0,0897	0,1372
McFadden R^2	0,0185	0,0002	0,0407	0,0016	0,0077	0,0026	0,0003
T-stat	1.2646	-0.1380	-1.8953	-0.2958	0.6804	0.3794	-0.1278
Spread S3	K=1	K=2	K=3	K=4	K=5	K=6	K=7
Pseudo-R^2	0,0169	0,0608	0,0768	0,0838	0,1146	**0.1696**	0,1651
McFadden R^2	0,0091	0,0075	0,0153	0,0139	0,0353	**0,0785**	0,0281
T-stat	-1.0522	-0.9609	-1.2951	-1.2439	-1.8462	**-2.5857**	-1.069
Spread S4	K=1	K=2	K=3	K=4	K=5	K=6	K=7
Pseudo-R^2	0,0405	0,0549	0,0676	0,0709	0,1145	0,1326	0,1455
McFadden R^2	0,0315	0,0017	0,0064	0,0015	0,0352	0,0437	0,0085
T-stat	-1.6782	-0.3926	0.8013	-0.3412	-1.5748	-1.789	-0.7698
Spread SF	K=1	K=2	K=3	K=4	K=5	K=6	K=7
Pseudo-R^2	0,0633	0,1049	0,1149	0,1123	0,0938	0,0901	0,1371
McFadden R^2	0,0532	0,0508	0,0525	0,0416	0,0153	0,0023	0,0001
T-stat	**-2.1343**	**-2.0284**	**-1.9253**	**-1.5951**	-0.9077	-0.3888	0.0695

Another issue is raised in analysing the goodness of fit. In the classical regression model, the coefficient of determination *R*2 is used as a measure of the explanatory power of the regression model. It can range in value between 0 and 1, with a value close to 1 indicating a good fit. In this kind of model it is no more likely to yield a *R*2 close to 1[15]. To avoid this problem we use the measure of fit proposed by Estrella (1998). It is a pseudo-R^2 in which the log-likelihood of an unconstrained model, L_u , is compared with the log-likelihood of a nested model, L_c [16]

$$\text{pseudo-}R^2 = 1 - (L_u / L_c)^{-(2/n)L_c}$$

A last potential problem stems from the serially correlation of the errors. Since the forecast horizons are overlapped, the prediction errors are in general autocorrelated. Thus, we correct this problem using the Newey-West (1987) technique and presenting thus t-statistics calculating using robust errors adjusted for the autocorrelation problem. Table 1 (panel 1) presents the Pseudo-R^2 calculated after the estimation of a probit model using the different spreads as explanatory variable and with lags ranging from 1 to 7 months. The highest pseudo-R^2 is obtained with the estimation of a probit model considering as predictor the spread S_3. In particular, the lag which presents the best fit is $k = 6$.

In this case, the pseudo-*R*2 is 0.169 and the t- This result is significant at the 5 percent level, and if we make a comparison with the pseudo - *R*2 of the other spreads we can draw the conclusion that the best recession predictor is the spread S_3 lagged six months. statistic is -2.585[17].

Indeed, some other spreads have also a significant measure of fit at 5 and 10 percent. The highest pseudo-R^2 is obtained with the estimation of a probit model considering

15 See, for example, Estrella , A.[1998]

16 The constrained model comes from a model with c1, in equation (1), is equal to zero. The log-likelihood in the case of the probit model is given by

$$L = \sum_t R_t \ln \Pr(R_t = 1 | X_{t-k}) + (1 - R_t) \ln \Pr(R_t | X_{t-k})$$

17 A value of 0:169 seems low if it is interpreted as an R^2 , but also in other empirical studies, the pseudo-R^2 is not very large. For example, Estrella and Mishkin (1998) yielded on U.S. data a value of 0:296 using as predictor the spread 10-year minus 3-month lagged four quarters and Frank Sédillot (2001) yielded on France data a value of 0.17 using the same definition of spread lagged six months.

as predictor the spread S_3. In particular, the lag which presents the best fit is $k = 6$. In this case, the pseudo-$R2$ is 0.169 and the t-statistic is -2.585. This result is significant at the 5 percent level, and if we make a comparison with the pseudo - $R2$ of the other spreads we can draw the conclusion that the best recession predictor is the spread S_3 lagged six months. Indeed, some other spreads have also a significant measure of fit at 5 and 10 percent.

As explained above, the probit model allows us to estimate the probabilities that the economy will be in recession in a given month on the basis of the interest rate spread observed some months before. Figure 6 presents an example of these probabilities using the domestic spread S_3 lagged 6 months and the foreign spread SF lagged 2 months.

Ideally, the probability should be one in the recession months (which are shaded in the figure) and zero otherwise. This chart shows that the estimated probability increases in the recession periods and remains low in the non-recession months.

6.3. Probit model with a lagged dependent variable

One of the main assumptions of the probit model is that the random shocks are independent, identically distributed normal random variables with zero mean. In this kind of model the errors are generally autocorrelated. In traditional time series approach we deal with this problem using an autoregressive moving average filter. Here, since the shocks are unobservable this technique is not more available. Therefore, we adopt the solution proposed by Dueker (1997) and Stock and Watson (2003b) to remove the serial correlation by adding a lag of R_t (the indicator variable of the state of the economy). Therefore, we allow the model to use information contained in the autocorrelation structure of the dependent variable to form predictions. The probit equation with a lagged dependent variable becomes:

$$\Pr(R_t = 1) = \phi(c_0 + c_1 X_{t-k} + c_2 R_{t-k})$$

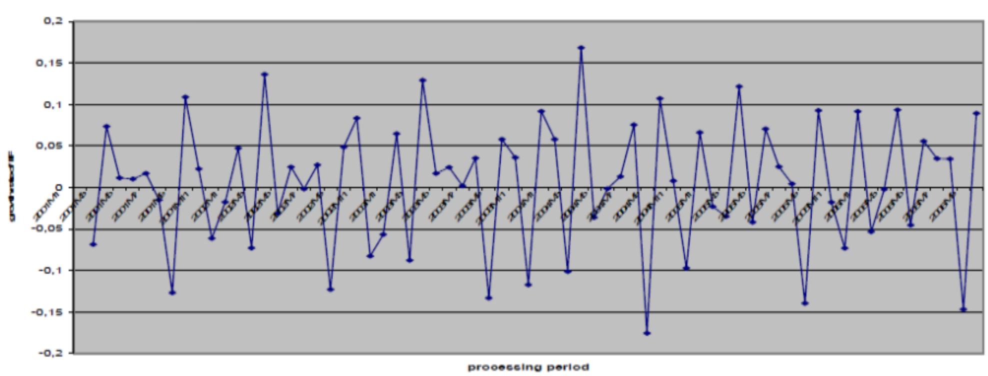
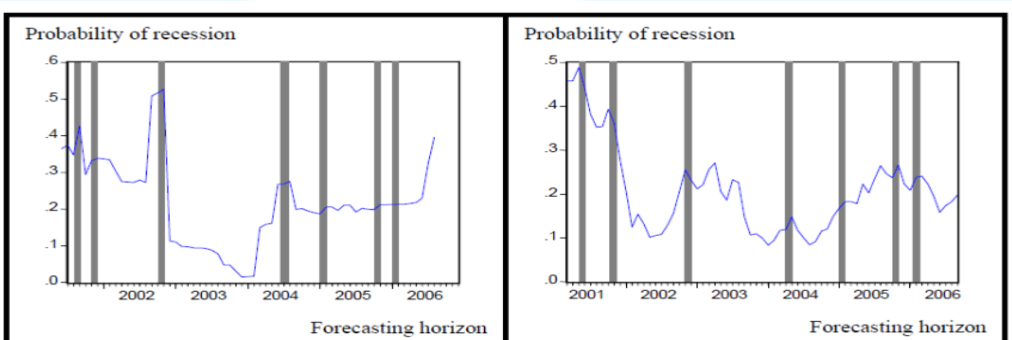


Chart 5 : Growth rate of real industrial production defining the dating of recessions



Estimated probability of a recession in the Tunisian industrial production in the current month using the spread S3 six months earlier.	Estimated probability of a recession in the Tunisian industrial production in the current month using the French spread (SF) two months earlier.

Chart 6 : the probabilities that the economy will be in recession in a given month

Table 2: measure of fit for recession predictions with Probit model with a lagged dependent variable

Probit model with a lagged dependent variable:

$$\Pr(R_t = 1) = \phi[c_0 + c_1 X_{t-k} + c_2 R_{t-k}]$$

(1) Nested model with only c_0
(2) Nested model with c_0 and c_1
(3) Nested model with c_0 and c_2

Spread S1		K=1	K=2	K=3	K=4	K=5	K=6
T-STAT	C_1	-0.826	-0.917	-0.762	-0.803	-1.482	-1.985
	C_2	2.375	-1.544	-0.190	-0.266	-1.191	-1.895
pseudo-R2	(0) / (1)	0,103	0,104	0,067	0,076	0,118	0,185
	(0) / (2)	0,084	0,045	0,001	0,001	0,020	0,064
	(0) / (3)	0,007	0,009	0,006	0,007	0,026	0,047
McFaddenR-squared		0,091	0,050	0,006	0,007	0,038	0,497
Spread S2		**K=1**	**K=2**	**K=3**	**K=4**	**K=5**	**K=6**
T-STAT	C_1	1.352	-0.246	-1.899	-0.299	0.670	0.324
	C_2	2.503	-1.617	-0.152	-0.168	-0.901	-1.651
pseudo-R2	(0) / (1)	0,116	0,096	0,103	0,071	0,099	0,1407
	(0) / (2)	0,089	0,043	0,001	0,001	0,01351501	0,052
	(0) / (3)	0,020	0,001	0,042	0,002	0,00751057	0,002
McFaddenR-squared		0,103	0,042	0,041	0,001997	0,020656	0,051
Spread S3		**K=1**	**K=2**	**K=3**	**K=4**	**K=5**	**K=6**
T-STAT	C_1	-0.879	-1.112	-1.320	-1.295	-2.033	**-2.827**
	C_2	2.394	-1.584	-0.224	-0.286	-1.216	**-2.065**
pseudo-R2	(0) / (1)	0,102	0,106	0,077	0,085	0,135	**0,236**
	(0) / (2)	0,085	0,045	0,001	0,001	0,021	**0,0692**
	(0) / (3)	0,006	0,011	0,016	0,015	0,044	0,099
McFaddenR-squared		0,090	0,052	0,016	0,015	0,055	0,143
Spread Sf		**K=1**	**K=2**	**K=3**	**K=4**	**K=5**	**K=6**
T-STAT	C_1	**-1.845**	**-2.189**	**-1.986**	**-1.703**	-1.127	-0.697
	C_2	2.249	-1.612	-0.395	-0.488	-1.319	-2.029
pseudo-R2	(0) / (1)	0,142	0,158	0,117	0,1154	0,115	0,148
	(0) / (2)	0,079	0,054	0,002	0,0031	0,021	0,059
	(0) / (3)	0,047	0,064	0,056	0,046	0,023	0,009
McFaddenR-squared		0,1285	0,104	0,055	0,044	0,036	0,059

Table 2 presents the results of the estimations of this model using respectively as explanatory variable the spread S1, S2, S3 and SF and with lags ranging from one to six . The pseudo-R2 is now calculated in the same manner as explained above with the exception that we can have three different specifications. The unrestricted model L_u is calculated using also the lag of R_t. The restricted model L_c can come from a model with both c_1 and c_2 are equal to zero, with only c_2 is equal to zero or with only c_1 is equal to zero.

In the first specification (first row of Table 2), the restricted model is the same as the simple probit model and therefore, it possible to compare this pseudo - *R*2 with the value obtained estimating the simple probit model. Now, the pseudo-R^2 is 0:236 for S_3 and the best recession predictor was obtained with the spread S_3 lagged six months[18]. However, this measure is sensible to the fact that we add another explanatory variable making thus the comparison not really meaningful. In the second specification (first row in Table 2), we test for the informational content provided by the lagged dependent variable in addition to the information embodied in the spread

The measure of fit is significant for the most leading spread at one to six months forecast horizon, in particular for S_3 (with k=6), suggesting that the lagged dependent variable provides also important information. In the last and most interesting case (last specification in first row of table 2), we test for the information content which goes beyond the information already contained in the autoregressive structure of the binary time series. The lag which presents the best fit is still k = 6 and the value of the pseudo-R^2 is 0.099, proving a good informative content of the spread.

The estimated probabilities of recession obtained from running this model give us the same pace of probability's curve indicating that in recession months there is an important likelihood of future decline in industrial activity.

Considering in-sample forecasting, it seems that the use of a lagged dependent variable helps to forecast historically recessions in the Tunisian economy.

Therefore, a probit model modified with the insertion of a lagged dependent variable appears somewhat preferable than the standard probit model. One disadvantage with in-

[18] For this case, the McFadden R-squared indicates the same result as the pseudo-R2. This is valid for the remaining spreads.

sample forecasts is that they allow the forecast to depend on data which were not available at the time of the forecast. As a result, the empirical results of the previous section may provide a misleading indication of the true ability of the yield curve to forecast real activity. By contrast, an out-of-sample forecast uses only information available to market participants at the time of the forecast. Moreover, an in-sample forecast can always be improved by adding a new explanatory variable, but that can lead to an over fitting problem. To avoid a possible misleading indication of the true ability of the term spread to forecast a recession it is important to carry out an exercise of out-of-sample forecasting. Specifically, forecasts for each period are based on an estimate of equation (2) and (7) using only data up to the previous period. For example, the forecast for 2005:M1 is estimated using coefficients from the regression estimated over the 2001:M1 to 2004:M12 period.

The quality of the out-of-sample forecast is evaluated using the Root Mean Squared Error (RMSE) statistic. The RMSE provides an estimate of the out-of-sample forecast error, and hence measures the accuracy of the forecast. The low the RMSE, the better the forecast. In evaluating the out-of-sample forecast power of the yield spreads, the RMSE from each yield spread forecast is compared with the RMSE of alternative forecasts of industrial production activity. Indeed, one advantage of the RMSE measure is that, for a given country, it can be compared across different forecasting models. In this section, the out-of-sample predictive power of the yield spreads model is compared with that of two alternative forecasting models aver range horizon. In the first alternative, equation (2) is used (called m1). In the second one, equation (7) is implemented (called m2), and in the third case we use a benchmark equation which is simply the identical equation (2) without the indicator variable and where past changes in t R are used to predict future changes.

To determine the relative forecast performance of the three models, the yield spread model, the lagged model and the combined yield spread plus lagged model were estimated across six forecast horizons and their relative out-of-sample RMSE's were compared for the three spreads: S1, S3 and SF.. Relatively to the two models (m1 and m2), we have three sets of RMSE for every horizon of forecasting. Thereafter, we return the RMSE of the equation m1 to the RMSE of the equation m3 and the RMSE of the equation m2 in the RMSE of the equation m3. If the report is lower to the unit, then the model m1 brings information in relation to the model m3[19]. The same reasoning makes itself for the model m2. Tables 6, 7 and 8 show the results of these model comparisons (m1 and m2).

For the equation (7) in witch S3 is the leading indicator, the model m1 outperforms the model m2 in 19 out of 30 cases and m2 outperforms m1 only 11 out of 30 cases. Otherwise, there are 10 out of 30 cases where the relative RMSE related to m1 is less than one. Whereas, there are only 7 out of 30 cases in witch the relative RMSE related to m2 is less than one. By considering the case of spread 2, the model m1 outperforms the model m2 in 19 out of 30 cases and m2 outperforms m1 only 11 out of 30 cases. In relation to m3, there are 73% cases where the relative RMSE related to m1 and that related to m2 are less than one and consequently the spread S1 is better than S2 as regard to the out-of-sample forecasting based in equation (7). Lastly, for the spread SF, the model m1 outperforms in all cases the model m2 and in each case of out-of-sample estimates, their relative RMSE are all less than one, suggesting that SF dominate the others two spreads concerning this criterion of robustness' dimension.

7. Summary and conclusion

This article has provided evidence on the ability of mainly Tunisian yield spreads to predict future real economic activity. Several interesting and important results were identified witch are broadly consistent with the results of previous studies, but are also more comprehensive in that they evaluate the predictive power of yield spread across multiple segments of the Tunisian yield curve. The results indicate the considering yield spreads are economically significant predictor of economic activity. Explanatory power begins to increase beyond five months for the spreads ten year minus one month and ten year minus one year, indicating that these two domestic spreads are the best leading indicators for Tunisian industrial production. In examining international financial linkages, the paper has also assessed the ability of the slope of the French yield curve to help predict growth in domestic activity. It has found that the French spread five year minus three month has information content in particular for long forecasting horizon.

The empirical results of this study also show, in sample estimates, that the strength of the relationship between the yield spreads and future economic growth varies across the different examined spreads. The predictive power is strongest in the case of spread ten years minus one month and in the case of French spread. Concerning the first spread, it consistently explains, in average, roughly 15 percent of the variation in future industrial production for forecasting horizon exceeding 6 month ahead. For the second spread, it explains 14 percent of the variation in future industrial production for forecasting horizon with 30 month ahead.

Considering the out-of sample forecasts, the results of this paper show that the best predictor of recession is the spread between 10-year and 1-month interest rates. Therefore, this specific yield spread can be useful for

[19] The relative RMSE compares the performance of a candidate forecast to a benchmark forecast, where both are computed using the pseudo out-of-sample methodology. See for example Stock and Watson (2001).

economic and monetary policy purposes. To arrive to this conclusion we used two non-liner model specifications to forecast the probability of a recession in the Tunisian economy. These are the standard probit model proposed by Estrella and Mishkin (1998) and the modified probit model with the addition of a lagged dependent variable proposed by Dueker (1997). We found that the use of a lagged dependent variable helps to forecast historically recessions in domestic context. Specific attention was paid on the accuracy of the forecast. We carried out an exercise of out-of-sample forecasting to investigate the out-of-sample performance of the probit models. The simple probit model (with the spread 10-year minus 1-month as explanatory variable) gives the best result at 6 months forecast horizon and performs better than the remaining spreads. With the addition of the lagged dependent variable in the probit model (with same spread) the forecasting ability improves significantly and beat the results related to a simple probit model. The different results carried out show that the spread 10-year minus 1-month could have provide useful information both to private investors and to policy Makers.

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Appendix

Table 1: Predicting future change in Industrial Production using the yield Spread S1
Sample: Monthly, 2001M1 to 2006M9

k (Months ahead)	Spread S1				
	c_1	c_2	$\overline{R}^2$	SEE	NOBS
1	0.028561	-0.326443	-0,01536	0.339292	67
	(0.368452)	(-0.069924)			
2	-0.005065	1.634079	-0,012631	0.155654	66
	(-0.106411)	(0.534829)			
3	-0.021254	2.533809	-0,004951	0.126886	65
	(-0.521641)	(0.929559)			
4	-0.008172	1.636745	-0,007111	0.090275	64
	(-0.242405)	(0.738618)			
5	-0.031451	2.967716	0,037973	0.065686	63
	(-1.089138)	(1.629789)***			
6	-0.041377	3.614858	0,08757	0.056728	62
	(-1.811085)	(2.522006)*			
7	-0.040329	3.597536	0,128601	0.047081	61
	(-2.526773)	(3.821367)*			
8	-0.035004	3.206183	0,15598	0.038087	60
	(-2.666530)*	(4.075803)*			
9	-0.033001	3.113668	0,126452	0.041569	59
	(-2.838866)	(4.239253)*			
10	-0.025297	2.590052	0,131807	0.034067	58
	(-2.404132)	(3.883054)*			
11	-0.021775	2.360778	0,11641	0.033316	57
	(-2.065799)	(3.567261)*			
12	-0.020789	2.305020	0,110936	0.033573	56
	1.930094	(3.711107)*			
18	-0.007439	1.524122	0,10694	0.023573	50
	(-0.745732)	(2.844720)*			
24	0.000836	1.050934	0,10534	0.017080	44
	(0.103163)	(2.642508)*			
30	0.009425	0.633171	0,071212	0.012749	43
	(1.527080)	(2.180401)			
36	0.011251	0.536042	0,141903	0.007915	32
	2.732678)	(2.240930)*			
40	0.007151	2.073985	0,172986	0.009095	28
	(0.846952)	(2.748280)*			

Notes: for this table and the following four ones, in parentheses are t-statistic after correction by method of Newe and West (1987) of standard errors that take into account the moving average created by the overlapping of forecasting horizons as well as conditional heteroskedasticity. Nobs. denotes the number of monthly observations.

$\overline{R}^2$ is the coefficient of determination adjusted for degrees of freedom, and SEE represents the corrected regression standard error.

*,** and *** significantly different respectively at 5%, 10% and 20%.

Table 2 : Predicting future change in Industrial Production using the yield Spread S2
Sample: Monthly, 2001M1 to 2006M9

k (Months ahead)	Spread S2				
	c_1	c_2	$\bar{R}^2$	SEE	NOBS.
1	-0.092998	9.448214	0.012743	0.334564	67
	(-0.819205)	(0.986859)			
2	-0.054486	6.103228	0.040012	0.151554	66
	(-0.925012)	(1.267880)			
3	-0.039552	4.762154	0.035515	0.124305	65
	(-0.909656)	(1.394460)***			
4	-0.027692	3.710145	0.046615	0.087834	64
	(-0.863132)	(1.477010)***			
5	-0.011875	2.259113	0.024142	0.066157	63
	(-0.510292)	(1.267491)			
6	0.001534	1.244261	-0.000903	0.059415	62
	(0.073300)	(0.789260)			
7	0.004080	1.094321	0.000126	0.050433	61
	(0.214297)	(0.731490)			
8	0.004506	0.959139	0.001978	0.041417	60
	(0.272726)	(0.756917)			
9	0.009980	0.548212	-0.012522	0.044754	59
	(0.574688)	(0.428083)			
10	0.009222	0.539107	-0.010739	0.036757	58
	0.568421	(0.467599)			
11	0.009067	0.533132	-0.010670	0.035632	57
	(0.582997)	(0.533739)			
12	0.011546	0.352021	-0.015300	0.035878	56
	(0.796306)	(0.381563)			
18	0.011800	0.366833	-0.013367	0.025110	50
	(0.940769)	(0.415334)			
24	0.009800	0.527779	0.005056	0.018012	44
	(0.987449)	(0.975668)			
30	0.009555	0.693174	0.065043	0.012791	43
	(1.118170)	(1.520594)***			
36	0.020411	-0.126487	-0.030883	0.008675	32
	(2.342449)	(-0.181893)			
40	0.030612	-1.124147			28
	(3.099600)	(-1.509807)***	0.064223	0.009675	

Table 3 : Predicting future change in Industrial Production using the yield Spread S3
Sample: Monthly, 2001M1 to 2006M9

k (Months ahead)	Spread S3				
	c_1	c_2	$\bar{R}^2$	SEE	NOBS.
1	0.040127	-0.858055	-0.015244	0.339273	67
	(0.328928)	(-0.138945)			
2	-0.016173	1.900730	-0.012367	0.155634	66
	(-0.218402)	(0.494080)			
3	-0.019297	1.969250	-0.010583	0.127241	65
	(-0.310614)	(0.588419)			
4	-0.010160	1.437126	-0.010617	0.090432	64
	(-0.200196)	(0.534318)			
5	-0.046242	3.166870	0.032614	0.065869	63
	(-1.100062)	(1.452202)***			
6	-0.057352	3.743228	0.070491	0.057256	62
	(-1.840154)	(2.293730)*			
7	-0.062412	4.024650	0.124043	0.047204	61
	(-3.079006)	(4.207805)*			
8	-0.060041	3.844991	0.176368	0.037625	60
	(-3.533284)	(4.919318)*			
9	-0.056027	3.659516	0.137313	0.041310	59
	(-3.249492)	(4.286884)*			
10	-0.045988	3.112719	0.150658	0.033695	58
	(-2.614346)	(3.465997)*			
11	-0.042987	2.949130	0.145526	0.032763	57
	(-2.613415)	(3.415131)*			
12	-0.039673	2.780708	0.127660	0.033256	56
	(-2.528343)	(3.463537)*			
18	-0.017474	1.699415	0.102936	0.023625	50
	(-1.232911)	(2.671469)*			
24	-0.010115	1.348513	0.144814	0.016699	44
	(-0.823207)	(2.688230)*			
30	0.001739	0.850233	0.116653	0.012433	43
	(0.183685)	(2.217399)*			
36	0.005618	0.662032	0.197963	0.007652	32
	(0.957595)	(2.619406)*			
40	-0.001017	1.017125	0.229135	0.008781	28
	(-0.165815)	(3.030234)*			

Table 4 : Predicting future change in Industrial Production using the yield Spread S4
Sample: Monthly, 2001M1 to 2006M9

k (Months ahead)	Spread S4				
	c_1	c_2	$\overline{R}^2$	SEE	NOBS.
1	0.075163	-7.118745	0.007777	0.335404	67
	(1.020785)	(-0.903606)			
2	0.047810	-3.659462	0.013828	0.153607	66
	(1.218631)	(-0.908563)			
3	0.036808	-2.368850	0.002809	0.126395	65
	(1.434029)	(-0.965206)			
4	0.032649	-1.938592	0.008733	0.089562	64
	(1.574795)	(-1.014981)			
5	0.017509	-0.139634	-0.016164	0.067509	63
	(1.219162)	(-0.116513)			
6	0.011499	0.754107	-0.008185	0.059630	62
	(0.931329)	(0.645521)			
7	0.011581	0.845981	-0.001909	0.050484	61
	(0.846719)	(0.648931)			
8	0.009731	0.952474	0.011200	0.041225	60
	(0.755149)	(0.747965)			
9	0.008164	1.261485	0.023950	0.043940	59
	(0.718992)	(1.084154)			
10	0.009032	1.037723	0.023981	0.036121	58
	(0.870445)	(0.925197)			
11	0.009115	0.995091	0.023499	0.035024	57
	(1.108764)	(1.061665)			
12	0.008367	1.089031	0.030666	0.035056	56
	(1.009878)	(1.197699)			
18	0.012607	0.597643	0.011272	0.024803	50
	(1.551316)	(0.776326)			
24	0.014476	0.420232	0.008573	0.017980	44
	(2.803968)	(0.897289)			
30	0.018316	0.100623	-0.023996	0.013386	43
	(4.164155)	(0.256913)			
36	0.014199	0.571974	0.183396	0.007721	32
	(5.725167)	(2.916400)*			
40	0.012239	0.776317	0.242489	0.008705	28
	(5.561178)	(3.313273)*			

Table 5 : Predicting future change in Industrial Production using the yield Spread SF
Sample: Monthly, 2001M1 to 2006M9

k (Months ahead)	Spread SF				
	c_1	c_2	$\overline{R}^2$	SEE	NOBS.
1	-0.056231	0.093156	0.000644	0.336608	67
	(-0.854896)	(1.186133)			
2	-0.028519	0.058171	0.014450	0.153559	66
	(-0.762165)	(1.258231)			
3	-0.025397	0.052536	0.021342	0.125215	65
	(-0.870170)	(1.429700)***			
4	-0.017013	0.041360	0.030258	0.088585	64
	(-0.729628)	(1.467212)***			
5	-0.006125	0.026561	0.018663	0.066342	63
	(-0.315525)	(1.187594)			
6	0.004548	0.014718	-0.002753	0.059470	62
	(0.343030)	(0.910613)			
7	0.009193	0.010112	-0.007696	0.050630	61
	(0.844627)	(0.770130)			
8	0.008940	0.009030	-0.006152	0.041585	60
	(0.835960)	(0.699909)			
9	0.009345	0.008983	-0.007872	0.044651	59
	(0.876219)	(0.748927)			
10	0.008146	0.009413	-0.001875	0.036596	58
	(0.789693)	(0.854738)			
11	0.010321	0.006632	-0.010252	0.035788	57
	(1.137264)	(0.700207)			
12	0.010484	0.006489	-0.001875	0.030497	56
	(1.070193)	(0.759976)			
18	0.005541	0.012471	0.047255	0.024347	50
	(0.792468)	(1.920736)**			
24	0.003683	0.014517	0.096609	0.021191	44
	(0.569158)	(2.312140)*			
30	0.011147	0.009878	0.142234	0.012252	43
	(1.863100)	(1.812424)**			
36	0.015745	0.004706	0.047428	0.008339	32
	(6.663353)	(1.597855)***			
40	0.014219	0.005843	0.055166	0.009722	28
	(5.505908)	(2.004496)*			

Table 6 : MODEL WITH RELATIVE LOWEST ROOT MEAN SQUARED ERRORR — SPREAD S3

k months ahead	Forecasting out-of-sample in months (M)						
	Model	1 M. Forecasting	3 M. Forecasting	6 M. Forecasting	9 M. Forecasting	24 M. Forecasting	36 M. Forecasting
k=1	MODEL m1	0,991	0,993	1,001	1,008	1,026	1,016
	MODEL m2	0,9979	1,001	1,008	1,014	1,032	1,021
		1 M. Forecasting	3 M. Forecasting	6 M. Forecasting	9 M. Forecasting	24 M. Forecasting	36 M. Forecasting
k=3	MODEL m1	0,991	0,997	1,006	1,011	0,984	0,999
	MODEL m2	0,990	0,996	1,005	1,010	0,983	0,998
		1 M. Forecasting	3 M. Forecasting	6 M. Forecasting	9 M. Forecasting	24 M. Forecasting	36 M. Forecasting
k=4	MODEL m1	0,968	0,998	1,009	1,002	0,993	1,028
	MODEL m2	1,012	1,035	1,046	1,039	1,036	1,067
		1 M. Forecasting	3 M. Forecasting	6 M. Forecasting	9 M. Forecasting	24 M. Forecasting	36 M. Forecasting
k=5	MODEL m1	1,013	1,034	1,049	1,043	1,017	1,025
	MODEL m2	0,995	1,020	1,039	1,032	1,011	1,026
		1 M. Forecasting	3 M. Forecasting	6 M. Forecasting	9 M. Forecasting	24 M. Forecasting	36 M. Forecasting
k=6	MODEL m1	0,989	1,017	1,036	1,029	1,02227872	1,014
	MODEL m2	0,991	1,018	1,037	1,030	1,02279405	1,015

Table 7 : MODEL WITH RELATIVE LOWEST ROOT MEAN SQUARED ERRORR — SPREAD S2

k months aheda	Forecasting out-of-sample in months (M)						
	Model	1 M. Forecasting	3 M. Forecasting	6 M. Forecasting	9 M. Forecasting	24 M. Forecasting	36 M. Forecasting
k=1	MODEL m1	0,973	0,977	0,983	0,980	0,987	0,999
	MODEL m2	0,980	0,985	0,991	0,987	0,995	1,007
	Model	1 M. Forecasting	3 M. Forecasting	6 M. Forecasting	9 M. Forecasting	24 M. Forecasting	36 M. Forecasting
k=3	MODEL m1	0,999	0,991	0,993	0,989	0,998	1,006
	MODEL m2	1,002	0,993	0,994	0,991	0,999	1,007
	Model	1 M. Forecasting	3 M. Forecasting	6 M. Forecasting	9 M. Forecasting	24 M. Forecasting	36 M. Forecasting
k=4	MODEL m1	0,958	1,027	0,984	0,981	0,993	1,001
	MODEL m2	0,979	0,989	0,992	0,989	0,998	1,006
	Model	1 M. Forecasting	3 M. Forecasting	6 M. Forecasting	9 M. Forecasting	24 M. Forecasting	36 M. Forecasting
k=5	MODEL m1	0,961	0,980	0,995	1,004	1,010	1,025
	MODEL m2	0,952	0,974	0,990	0,985	1,008	1,025
	Model	1 M. Forecasting	3 M. Forecasting	6 M. Forecasting	9 M. Forecasting	24 M. Forecasting	36 M. Forecasting
k=6	MODEL m1	0,900	0,939	0,966	0,958	1,004	1,035
	MODEL m2	0,9013	0,939	0,965	0,957	1,002	1,032

Table 8 : MODEL WITH RELATIVE LOWEST ROOT MEAN SQUARED ERRORR — SPREAD SF

k months ahead	Forecasting out-of-sample in months (M)						
	Model	1 M. Forecasting	3 M. Forecasting	6 M. Forecasting	9 M. Forecasting	24 M. Forecasting	36 M. Forecasting
k=1	MODEL m1	0,959	0,972	0,984	0,979	0,986	0,985
	MODEL m2	0,9724	0,987	0,999	0,993	0,999	0,999
	Model	1 M Forecasting	3 M Forecasting	6 M Forecasting	9 M Forecasting	24 M Forecasting	36 M Forecasting
k=3	MODEL m1	0,935	0,957	0,979	0,972	0,995	0,993
	MODEL m2	0,937	0,958	0,980	0,973	0,995	0,999
	Model	1 M Forecasting	3 M Forecasting	6 M Forecasting	9 M Forecasting	24 M Forecasting	36 M Forecasting
k=4	MODEL m1	0,901	0,936	0,958	0,952	0,977	0,982
	MODEL m2	0,912	0,946	0,967	0,961	0,985	0,988
	Model	1 M Forecasting	3 M Forecasting	6 M Forecasting	9 M Forecasting	24 M Forecasting	36 M Forecasting
k=5	MODEL m 1	0,946	0,973	0,989	0,983	0,991	0,995
	MODEL m2	0,960	0,985	0,999	0,994	0,992	0,996
	Model	1 M Forecasting	3 M Forecasting	6 M Forecasting	9 M Forecasting	24 M Forecasting	36 M Forecasting
k=6	MODEL m1	0,960	0,979	0,993	0,987	0,992	0,993
	MODEL m2	0,963	0,982	0,997	0,991	0,996	0,998