Forecasting Recessions Using Financial Variables
The French Case

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Forecasting Recessions Using Financial Variables
The French Case

Francis Bismans and Reynald Majetti *

Abstract

In this paper, we focus on the ability of two financial variables – the yield curve spread and the EUR/USD exchange rate – to predict French recessions over the period 1979-2009. First, we propose a turning point chronology for the French business cycle based on a classical conception of economic cycles and a non-parametric dating algorithm applied to the real GDP series. Second, static and dynamic probit models are developed and estimated to produce the recession probabilities. In-sample results reveal both a strong predictive content of the two financial variables and the superiority of the dynamic specification in forecasting whether or not the French economy will be in recession. Out-of-sample results finally show the performance of the dynamic model in predicting the latest recession occurred in 2008.

Keywords: French business cycle, dynamic probit, recession forecasts, term spread, EUR/USD exchange rate

JEL Classification: C22, C25, E32, E37

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1 Introduction

Predicting sudden modifications or more exactly turning points in the business cycle is very useful for central bankers, entrepreneurs and governments. But how measuring economic activity? Following Burns and Mitchell (1946, p.73), aggregate activity “can be given a definite meaning and made conceptually measurable by identifying it with gross national product.” The problem is then to identify the ups and downs in quarterly real GDP. Two great sets of methods are available to analyse GDP: first detrending the series to isolate its cyclical component, by using linear deterministic trend, first order differencing, phase-averaging, filters such as that of Hodrick-Prescott, Baxter-King or band-pass, etc.; secondly there exists mechanical dating rules, e.g. the rule of the two consecutive quarter declines in GDP as an indicator of recession, or Bry-Boschan dating algorithms (see Harding and Pagan, 2002, p. 373sq). This last approach has our preference, because, as shown by Canova (1994), the various trend-removal procedures induce different properties in the moments of the considered series. Consequently, we define in first approximation a peak (through) of the cycle as a local maximum (minimum) in the real GDP measured quarterly in level.

The prediction of turning points is carried out using either an econometric model or composite leading economic indicators (CLI). This latter has been originally proposed in 1938 by Burns and Mitchell, more generally by the NBER, based on their capability to lead the business cycle. Today they are currently employed by OECD (2002) for example. From this viewpoint, a common rule to identify turning points is that of three consecutive declines: a downturn is imminent when CLI is declined for the third consecutive time. An alternative methodology to CLI’s is to use econometric models. Within this approach, two ways to cope with the problem of predicting downturns are possible: one is to rely on models built to forecast future values of economic variables, here GDP, so that turning points are a by-product of forecasting activity; the other is to construct an econometric model that predicts directly the downturns. This last approach is pioneered by Estrella and Hardouvelis (1991) and forcefully used by Estrella and Mishkin (1997, 1998), Chin et al (2000), Chauvet and Potter (2005), Moneta (2005) and Nyholm (2007). Instead a set of linear or non linear regressions these authors are useful themselves of a probit or logit model, what yields directly the probabilities of recession.
All those methods have their advantages and their disadvantages. CLI’s are cheap and easily available forecasting tools. However, as explained by Hendry and Clements (1998, chapter 9), the construction process of leading indicators ignore the time series properties of their components, including non-stationarity and cointegration. Above all leading indicators are selected based on their ability to forecast past downturns, i.e. recessions that have already occurred. On the other hand, their ability to predict future recessions is very limited. That is, which explained that the indicators list is periodically revised. At last, CLI’s are atheoretical implement: as it says De Jong (1991, p. 15), they are “perhaps the least theoretical of forecasting tools.” The consensus on the utility of econometric models – structural in the Cowles Foundation tradition or vector autoregression models – is that those have a weak predictive power. It is undoubtedly for this reason that the use of probit models was spread quickly. In such models the variables included as regressors are selected on the basis of their ability to determine the probabilities of past recessions. In fact, in the quoted papers, these variables are reduced to only one: the yield curve, i.e. the spread between long-term and short-term interest rates. Such an approach has equally its insufficiencies: its strength – forecasting directly downturns – is also its weakness, because recessions are not very frequent events, which makes delicate the statistical inference procedures. However, many studies – see e.g. Del Negro (2001) – show the predictive superiority of probit models compared to the econometric models or leading indicators.

Our purpose in this paper is to develop and estimate a generalized probit model ready to predict most exactly possible the recessions. It differs from the majority of the existing models from a double point of view: first it is about a truly dynamic model; then this model rests on precise theoretical foundations.

As far as the first point is concerned, most studies – exceptions are Dueker (1997), Chauvet and Potter (2005), Kauppi and Saikkonen (2008) and Startz (2008) – use a static probit model to forecast downturns. Formally, consider the binary variable \( R_t \), which takes value one in recessions and zero otherwise, and \( x_t \), a vector of explanatory variables (or predictors), with \( t = 1, \ldots, T \). (Of course, this vector may include lagged values of the explanatory variables.) In the probit model, \( R_t \) is related to the regressors by
\[ E(R_i \mid x_i) = \Pr(R_i=1 \mid x_i) = \Phi(x_i'\beta) = \Phi(z_i), \]  

where \( E(\cdot) \) denotes mathematical expectation (The operator expectation is denoted by \( E \) and not by \( E \), because this last letter will be used further to indicate the rate of exchange.) Furthermore, \( \Phi(\cdot) \) is the distribution function of a standard normal variate.

To introduce dynamic probit model, we define information set \( I_t = \{ R_t, \cdots, R_i, x_t, \cdots, x_1 \} \). The dynamic analogue of (1) is then

\[ E(R_i \mid I_{t-1}) = \Pr(R_i=1 \mid I_{t-1}) = \Phi(z_i), \]  

where

\[ z_i = \sum_{j=1}^{\rho} \gamma_j R_{t-j} + x_i'\beta. \]  

The model defined by (2)-(3) is a simplified form of the Binary Autoregressive model, BARX(\( \rho \)), suggested by Zeger and Qaqish (1988). If we are not mistaken, the first economic paper to use a dynamic probit is that of Eichengreen et al. (1985). (For a quick survey of the economic and econometric literature on the subject, see de Jong and Woutersen, 2007.)

Secondly, for what concerns the foundations of our model, we retained two financial variables among the regressors: the yield curve and the exchange rate between euro and US dollar.


Several theoretical explanations for the link between the yield spread and future growth have been advanced. The first of these reaches back to Fisher (1907). It is based on the idea that the term structure – i.e. the differential between long-term and short-term interest rates – contains useful information concerning market expectations of future real activity. Suppose households expect real income to decrease in the future because of a prevision of recession. The expectation of reduced future income will increase today’s demand for long-term bonds which pay off in the future. The growing demand for the long-term bonds will cause the price of these bonds to increase, or their yield to fall. Consequently, the yield curve weakens as long-term interest rates diminish. As long as these
expectations for economic growth are at least partially realised, a weakening of the yield curve will be associated with a future decrease in real economic activity.

Another explanation uses the expectations theory of the term structure of interest rates. For this approach long-term rate equals to the weighted mean of the expected future short rates, except for a risk premium. Expectations of weak growth imply monetary policy slackening and future decreases in the short-term interest rate. These decreases express in today’s long-term rates.

Finally, the yield spread may reflect the stance of monetary policy. When monetary policy is tightened, short-term interest rates rise; long-term rates also typically rise but usually by less. As a result, the yield spread narrows or even turns negative. In time, higher interest rates reduce spending in the interest-rate sensitive sectors of the economy, causing economic growth to slow. Thus a small, or negative, yield spread will be associated with slower real economic growth in the future.

The second variable introduced in the analysis is the exchange rate between US and French economies. Define this (spot) rate as the home-country price of the foreign currency. In our context, France is the home country. Thus the nominal parity EUR/USD is measured by the number of US dollars offered for one euro. With this convention, a rise (decrease) of this bilateral exchange rate is equivalent to an appreciation (depreciation) of euro and depreciation (appreciation) of the dollar.

It is well-know in open-economy macroeconomics that an increase in the exchange rate of a country diminishes, at least in the long run, the net exports, i.e. the difference between exportations and importations of a country. (Explanation is founded on a simple argument: all else equal, an appreciation of a country’s money yields its goods more expensive for foreign consumers and producers.) In the short run this effect is more ambiguous due to the presence of a J-curve phenomenon. In fine, we thus can postulate a negative relation between gross domestic product and exchange rate of a country.

However exchange rate itself is linked to interest rates by interest parity relations. Covered interest parity relationship defines forward exchange rate at time $j$ as

$$s_j^f = s_t + j(r_t^s - r_t^f),$$

(4)
where $s_t$ is the natural logarithm of the spot exchange rate between the euro and the dollar at time $t$, $s_t^j$, $j \geq 1$, is the natural logarithm of the forward EUR/USD exchange rate period $t$ for delivery in period $t + j$ and $r_t^*$ and $r_t^j$ denote respectively the foreign-country and home-country interest rates, continuously-compounding, on riskless $(t + j)$-period securities. Under the assumption of rational expectations, the forecast of the exchange rate $s^e_{t+j}$ by agents in $t$ is equal to the mathematical expectation of the probability distribution of $s_{t+j}$ given the information possessed in period $t$:

$$s^e_{t+j} = E(s_{t+j} | \Omega_t),$$

where $\Omega_t$ denotes the information set available to agents at time $t$.

Substituting (5) for $s^e_t$ in (4) then gives

$$s^e_{t+j} - s_t = j(r_t^* - r_t^j).$$

In other words, the expected variation of the exchange rate over the horizon $j$ should be equal to the difference in interest rates for time of maturity $j$. Such a relationship is precisely uncovered interest parity hypothesis (UIPH). Empirical evidence generally rejects UIPH – for a survey, see Isard (2005) –, although Chinn and Meredith (2004) do not reject it using interest rates on long maturity bonds. At all events, UIPH is a component of almost all the exchange rate models. Following this stream we will adopt the assumption of uncovered parity. We will make it more especially as recent research by Krippner (2006a, 2006b) showed how UIP is related to the yield curve.

The rest of this article is structured as following. Section 2 uses a variant of the Bry-Boschan’s algorithm to date the French business cycle. Section 3 is devoted to the presentation of the data and development of the probabilistic model to be estimated. Section 4 presents empirical results and discusses the points relevant to forecasting of the cyclical downturns. Section 5 achieves an out-of-sample prediction of the 2008 recession. Last section summarizes, concludes and presents perspectives for future research.
2 Dating the French Business Cycle

At this point, we are interested in defining and dating the French business cycle for the period 1979Q1 – 2009Q3. The basic idea consists in locating “turning points” in the “aggregate economic activity”. To proceed, three problems must be resolved. The first is central and concerns the definition of business cycle fluctuations. The second is relative to the macroeconomic time series chosen to represent the “aggregate economic activity”. The responses to the two first questions will lead us to choose a parametric or non-parametric dating model.

2.1 Defining the Business Cycle

We can distinguish three conceptions of a cycle: the classical cycle, the growth cycle and the acceleration cycle.

The first refers to the traditional conception of the business cycle defined by Burns and Mitchell (1946, p.3): “Business cycles are a type of fluctuation found in the aggregate economic activity of nations … a cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general … contractions …”. Following this approach, turning points have to be located in the level of time series chosen to represent the aggregate economic activity so that classical cycle is described by a series of expansion and recession phases. Specifically, an expansion (resp. recession) phase corresponds to the period of time between a trough (resp. a peak) and a peak (resp. a trough).

The conception of growth cycle was introduced by Mintz (1969). Turning points are now located in detrended time series. The distinction between levels and detrended series is crucial. Indeed, in a growth cycle, a recession does not imply that the growth is negative during all the phase, but simply means that the growth is inferior to the long term or potential growth. Moreover, there are enormous number of ways of detrending: first-differencing, “phase-averaging” as described in Boschan and Ebanks (1978), Hodrick-Prescott filter, band-pass filters (Baxter-King or Christiano-Fitzgerald among others)… So, this creates a major inconvenient: business cycle depends on the filter chosen1.

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The *acceleration cycle* is the most recent conception and refers to the variation of the growth rate of economic activity\(^2\). So, one can distinguish phases where the growth rate is increasing or decreasing. To some extent, this makes expansion or recession phases more complex, leading to a higher reproduction frequency and a more volatile cycle. As a consequence, analyzing (in real time) and forecasting economic fluctuations become more difficult.

Insofar as our main objective is to predict French recessions by financial variables, the traditional conception (*classical cycle*) appears to be the more appropriate to establish a reference chronology for the French business cycle.

### 2.2. Measuring the “Aggregate Economic Activity”

Burns and Mitchell (1946, p.72-73) gave a precise answer to that question: “Aggregate activity can be given a definite meaning and made conceptually measurable by identifying it with gross national product”. However, since data on Gross Domestic Product (GDP) was not available to them, for either the time period or frequency in which they were interested, they used many series to define the concept of *monthly* “aggregate economic activity”.

Describing business cycles is more difficult if multiple series are used rather than a single one. Indeed, as referred by Burns and Mitchell (1946), the methodology is a two-stage one. First, one needs to locate turning points in each selected series by graphical methods, thereby defining *specific cycles*. Second, a *reference cycle* is extracted in such a way that peaks and troughs of the different specific cycles cluster around. So this requires being able to measure the tightness of clusters of turning points and the degree of synchronization between each *specific cycle* and the *reference cycle*, see e.g. Harding and Pagan (2006). This is then the latter which is called a business cycle. For example, NBER’s Dating Committee employs this approach when it is matter of locating US business cycle fluctuations. More precisely, they define a recession phase in a *classical cycle* as a “significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production and wholesale-retail sales”.

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Following the classical definition of Burns and Mitchell (1946), we will only use the real GDP$^3$ $y_t$ as macroeconomic time series in order to construct the French business cycle. Now, it remains to describe the dating model.

### 2.3. Dating Model for Business Cycle Fluctuations

The methods for describing and dating any cycles are separated in two types. On the one hand, Bry and Boschan (1971) have proposed a non-parametric method for locating turning points in monthly time series. Through an automated dating algorithm (BB algorithm), they aim at reproducing complex rules and judgmental procedures of the NBER’s Dating Committee. Harding and Pagan (2002) have also extended BB algorithm in a quarterly version named BBQ. Notice that these non-parametric procedures do not require any knowledge of the data generating process (DGP) for the underlying series and they clearly lead to identify *classical cycle*. On the other hand, parametric models require specifying the DGP and using it to locate turning points in time series. The most commonly used is that of Hamilton (1989) where the growth rate of a macroeconomic time series is treated as a Markov Switching (MS) process. Basically, the model specifies two regimes in the economy by introducing a latent binary state variable. One sometimes imposes a negative growth rate for the low-regime in order to represent a *classical cycle*.

Unlike to the United States, there exists neither reference conception nor reference chronology for the French business cycle and more generally for all the European countries (see e.g. Anas *et al.* 2006). Various works have been realized by official agencies and academic researchers. So one can find representation of *classical cycle* (CEPR, ECRI, COE-Rexecode), *growth cycle* (OECD) and *acceleration cycle* (ECRI). Various measures of “aggregate economic activity” have also been proposed, like GDP, industrial production, employment, private consumption and others. As we have mentioned above, our approach involves both a classical conception of business cycle and the real GDP as a measure of “aggregate economic activity”. To the extent that the time frequency is quarterly, we adopt the methodology of Harding and Pagan (2002) to locate the turning

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$^3$ For the period 1979Q1 – 2009Q3, the real French GDP was obtained from the Bank of France. $y_t$ refers to the logarithm of real GDP since the log transformation does not modify the pattern in the series.
points of cycle. The automated dating algorithm BBQ is performed in *Visual Basic under Excel*, and it can be decomposed in three key components:

1. Identify a potential set of peaks and troughs by the application of a “turning point rule”. Let’s denote $y_t$ the logarithm of real GDP at quarter $t$. So, a local peak (resp. trough) is reached at time $t$ if and only if $\{y_t > y_{t+k}\}$ (resp. $\{y_t < y_{t+k}\}$) for $k = 1, 2$.

2. Enforce the condition that peaks and troughs must alternate by selecting the highest (resp. lowest) consecutive peaks (resp. troughs).

3. Turning points are censored according rules mainly relative to the duration of phases and cycles. So an expansion or recession phase must be at least 2 quarters long. A complete cycle, defined by the period of time between two peaks or two troughs, must be at least 5 quarters in length. Complementary rules are finally designed to avoid spurious turning points dating at the ends of the series.

The French business cycle is thus obtained by application of BBQ to the real GDP series. In figure 1, we show the empirical results and it appears that three recessions occurred in France for the period 1979Q1 – 2009Q3. The first coincided with the *second oil crisis* and it lasted from 1980Q2 to 1980Q4. The shortest recession arose in 1992Q4 and it only lasted two quarters (the minimum phase length). After the reunification of Germany, high interest rates had been maintained in the major European economies, particularly in France which experienced a decline of investment. Finally, the last one is the most important both in duration and amplitude: beginning in 2008Q2, the recession is still present at the end of 2009. This is the consequence of the *mortgage subprime crisis* initially localized in United States at summer 2007. By the way of financial liberalization and expansion of credit, this has triggered an international financial crisis. The contagion process that then followed hurts not only the France but also a great number of emergent and advanced economies.
Figure 1. French Business Cycle

Note: Real GDP represents the French “aggregate economic activity”. Business cycle’s turning points are then localized by application of BBQ algorithm. Shaded regions depict recession periods.

3 Data and Empirical Model

In this section, we firstly present the data used in our empirical analysis. Secondly, the dynamic probit model and its estimation will be described.

3.1 The Data

Our empirical application requires three variables: a recession indicator \( R_t \), the yield curve spread \( S_t \) and the spot exchange rate between euro and US dollar \( E_t \).

The recession indicator \( R_t \) can be distinguished by its nature, in the sense that it is a constructed binary time series. As described in the previous section, the application of BBQ algorithm to the real GDP series enables us to locate the turning points of the French business cycle. So this variable takes only two values: 1 if the French economy is in recession (at quarter \( t \)) and 0 otherwise.

The two next are financial variables and they were obtained from the OECD’s website. The yield curve spread \( S_t \) is defined as the difference between the 10-year government bond yield and the 3-month PIBOR. The EUR/USD spot
exchange rate \( (E_r) \) expresses the price of one euro in terms of US dollars. So, if we consider the euro (US dollar) as the domestic (foreign) currency, \( E_r \) refers to an indirect exchange rate. (More detail on the series can be found in appendix A).

Concerning the periodicity, one can underline an important dissymmetry between these two types of series: financial variables are indeed quoted in a continuous time whereas data on GDP are at best quarterly available. Thus, for our study, all the data have been collected quarterly and the sample period extends from the first quarter of 1979 to the third quarter of 2009. Given that the EUR/USD exchange rate has only been reconstituted since the beginning of the European Monetary System – in fact by using the European Currency Unit (ECU) for the period 1979-1999 – we are constrained by starting in 1979Q1. In the same way, the GDP is always known with a certain lag (almost one full quarter) so that the last available value was in 2009Q3 at the time we realized our analysis.

3.2 The Dynamic Probit Model

In line with equations (1)-(3), we define the empirical model as

\[
Pr(R_t = 1) = \Phi \left( \gamma_0 + \sum_{j=1}^{p} \rho_{r,j} R_{t-j} + \gamma_2 S_{t-k_2} + \gamma_2 E_{t-k_2} + u_t \right), \quad t = 1, \cdots, T, \tag{7}
\]

where, recall it, \( R_t \) is a dummy with \( R_t = 1 \) if the economy is in recession in period \( t \) and \( R_t = 0 \) otherwise, \( \Phi(\cdot) \) is the standard normal CDF, \( S \) and \( E \) are predetermined variables, respectively the yield spread and exchange rate Euro/US dollars, \( u_t \) is a perturbation with errors possibly correlated and/or heteroskedastic, and \( k_1, k_2 \) are parameters of forecast horizons.

Let \( \rho = (\rho_1, \cdots, \rho_p, \gamma_0, \gamma_1, \gamma_2) \) denote the true parameters of the probit model, \( \rho \in \mathbb{R}^p \), \( \gamma = (\gamma_0, \gamma_1, \gamma_2) \in \mathbb{R}^3 \), \( R_{-p} = (R_{-1}, \cdots, R_{-p}) \in \mathbb{R}^p \), \( x_{-1} = (1, S_{t-k_1}, E_{t-k_2}) \).

Assuming the normality of perturbations, the loglikelihood function conditional on the first observations \( R_{-p} \) is

\[
\ln L(\hat{\beta}_t) = (T-p)^{-1} \sum_{t=p+1}^{T} \ln L_t(\hat{\beta})
\]

\[
= (T-p)^{-1} \sum_{t=p+1}^{T} \left[ y_t \ln(\Phi(\rho' R_{t-p} + \gamma' x_{-1})) + (1 - y_t) \ln(1 - \Phi(\rho' R_{t-p} + \gamma' x_{-1})) \right]. \tag{8}
\]

The optimisation of the highly nonlinear likelihood function (8) can be carried out by standard numerical algorithms. Furthermore De Jong and Woutersen (2009) have proved that, given standard conditions, specially near epoch.
dependence of the random variables $R$, the maximum likelihood estimator $\hat{\beta}$ is consistent so that

$$\hat{\beta} \xrightarrow{p} \beta.$$ 

Under another assumption, de Jong and Woutersen (2009, theorem 4) also proved that

$$T^{1/2}(\hat{\beta} - \beta) \xrightarrow{D} N(0, I^{-1}),$$

where $I^{-1}$ is the inverse of the usual information matrix.

### 4 Empirical Results

In-sample results are based on estimation and forecasting procedures over the entire sample period. The first step of the analysis consists in determining the optimal lag order of the predictors. Next, the estimation of static and dynamic probit models will permit us to assess their in-sample performance in forecasting French recessions.

#### 4.1 Lag Order Selection

The optimal lag order for the financial variables and the lagged recession indicators will be respectively selected on the basis of static and dynamic models.

Let us consider the dynamic probit model (7). The static specification is simply obtained by deleting the lagged dummies on the right-hand side so that it contains only two regressors – the interest rate spread $S_{t-k_i}$ and the EUR/USD exchange rate $E_{t-k_j}$. Then, we can determine the optimal lag orders $k_1^*$ and $k_2^*$ using the pseudo $R^2$ measure of fit developed by McFadden (1979):

$$\text{pseudo } R^2 = 1 - \frac{\ln L(\hat{\beta})}{\ln L(\hat{\beta}_0)},$$

where $L(\hat{\beta})$ denotes the unconstrained maximum likelihood as a function of the vector of parameter estimates and $L(\hat{\beta}_0)$ the maximum value under the constraint that all parameters are 0 except for the constant.

This measure is comparable to the coefficient of determination in the linear regression case and it takes values between 0 ("no fit") and 1 ("perfect fit"). The pseudo $R^2$ values for static models are computed with $k_1$ and $k_2$ varying between
1 and 4 quarters. The results, displayed in table 1, indicate that the best in-sample fit is obtained by applying the third lag of $S_i$ and the second lag of $E_i$ as regressors.

Table 1. Pseudo $R^2$ Measures for Static Probit Models

<table>
<thead>
<tr>
<th>$k_1$</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.5214</td>
<td>0.5871</td>
<td>0.6579</td>
<td>0.6125</td>
</tr>
<tr>
<td>2</td>
<td>0.5691</td>
<td>0.6176</td>
<td>0.6952</td>
<td>0.6505</td>
</tr>
<tr>
<td>$k_2$</td>
<td>3</td>
<td>0.5503</td>
<td>0.5812</td>
<td>0.6332</td>
</tr>
<tr>
<td>4</td>
<td>0.5663</td>
<td>0.5674</td>
<td>0.5817</td>
<td>0.5456</td>
</tr>
</tbody>
</table>

Note: The table presents the pseudo $R^2$ values for the static probit model $Pr(R_i = 1) = \Phi(\gamma_0 + \gamma_1 S_{i-k_1} + \gamma_2 E_{i-k_2} + u_i)$ with different choices for the lag orders $k_1$ and $k_2$. All the results are computed from the entire sample period 1979Q1 – 2009Q3.

Once $k_1^*$ and $k_2^*$ established, we proceed to the determination of the optimal lag order of the recession indicator, namely $p^*$. Basically, the model is now dynamic and the underlying method is different from the preceding case. Since the number of regressors is varying according to the number of lagged indicators, the pseudo $R^2$ would be inappropriate to evaluate the in-sample performance of the different dynamic models in that there might exist a problem of overfitting. Indeed, the more variables a model includes, the better the in-sample results. Nevertheless, the use of too many explanatory variables in the regression can undermine the predictive power of a parsimonious model. Thus, one could turn to information criteria for the determination of $p^*$. The Akaike information criterion (AIC), the Schwarz Bayesian information criterion (BIC) and the Hannan-Quinn criterion (HQC) are computed from the estimation of the dynamic model (7) with $k_1 = 3$, $k_2 = 2$ and $p$ changing between 1 and 4 quarters. The results are reported in table 2. It appears clearly that $p = 1$ leads to minimize the three criteria so that the best choice for our dynamic probit model is to use the only first lag of the binary indicator. One can also remark that these criteria favor the more parsimonious model and reveal a potential overfitting problem in adding several lags of $R_i$ among the regressors.
Table 2. Information Criteria for Dynamic Probit Models

<table>
<thead>
<tr>
<th>Information Criterion</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
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</thead>
<tbody>
<tr>
<td>AIC</td>
<td>21.155</td>
<td>28.875</td>
<td>30.819</td>
<td>27.821</td>
</tr>
<tr>
<td>SBC</td>
<td>38.305</td>
<td>42.813</td>
<td>47.544</td>
<td>47.275</td>
</tr>
<tr>
<td>HQC</td>
<td>31.683</td>
<td>34.535</td>
<td>37.612</td>
<td>35.720</td>
</tr>
</tbody>
</table>

Note: The table presents the information criteria values for the dynamic probit model with different choices for the lag order  \( p \). All the results are computed from the entire sample period 1979Q1 – 2009Q3.

4.2 In-Sample Forecasting

In this section, we examine the estimation results of the dynamic probit model considering the optimal lag orders previously established. In comparison, it would also be worthwhile to analyze the ones of the static specification. These results are summarized in table 3. Column 1 shows the results for the static probit model using the third lag of  \( S_t \) and the second lag of  \( E_t \), while in column 2 the dynamic model adds  \( R_{t-1} \) beside these two financial predictors.

First of all, it emerges that in both models the coefficient estimates of  \( S_t \) and  \( E_t \) are statistically significant at the 1% level. They also have the expected sign, respectively negative for the interest rate spread and positive for the EUR/USD exchange rate, meaning that a flattening (or inversion) of the yield curve and/or an appreciation of the euro against US dollar will lead to a higher probability of recession in France. The predictive content of these two financial variables does not vanish if the dynamic feature is included in that the associated parameters stay particularly significant. We obtain a positive and statistically significant estimate for the coefficient of the lagged recession indicator. So, the likelihood of a recession in the current quarter would be much higher if the economy was already in depression in the previous quarter. This result coincides both with the idea of a persistence phenomenon and the rule according to which a recession must last a minimum of 2 quarters. The additional predictive power of  \( R_{t-1} \) in predicting French recessions produces a better in-sample fit as it is shown by the pseudo  \( R^2 \) and the RMSE measures. Notice that the pseudo  \( R^2 \) values are particularly high.
for the two models. Among the three information criteria, the AIC and HQC favors the dynamic model, while the BIC leads us to choose the more parsimonious specification.

To further illustrate the in-sample performance of these models in forecasting French recessions, figure 2 shows the actual recessions (shaded areas) and the estimated probability of recession at each quarter \( t \) for the period 1979Q1 – 2009Q3. These probabilities follow from the estimated parameters of table 3 and the values of considered predictors. Some interesting observations come out from these two graphs. First, the estimated probabilities match quite very well with the true periods of depression. All of them are preceded by a sudden increase in the recession probabilities reaching more than 85% at the height of depression and then they experience a drop before return to economic growth. This suggests an excellent in-sample fit of our models, as previously seen with the marked pseudo \( R^2 \) values. Second, the dynamic probit produces a better in-sample fit in that it allows reducing spurious signals. For instance, the probability of recession with the static model reaches about 53% in the second quarter of 1991 whereas the economy is in expansion. A more precise observation of the financial series reveals in fact an inverted yield curve and an appreciation of euro against US dollar during 1990 (see figures A.1 and A.2. in appendix A). So, these two combined effects explain the sudden increase in the recession probability in the beginning of 1991. The inclusion of \( R_{t-1} \) among the regressors leads to a significant decline of this probability up to 32%. Finally, spurious signals may be due to the highest volatility and/or extreme values of financial variables in comparison with the ones of macroeconomic indicators. For example, the strong negative term structure of interest rates at the end of 1992 accounts for the raising of the probability just after the 1992-93 recession.

As a whole, two main results emerge from the in-sample exercise. One the one hand, the interest rate spread and the EUR/USD exchange rate have a great predictive content about whether or not the French economy will be in recession. On the other hand, the dynamic specification improves the performance/accuracy of the static one in forecasting recessions.
Table 3. In-Sample Estimation

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Static Probit</th>
<th>Dynamic Probit</th>
</tr>
</thead>
<tbody>
<tr>
<td>constant</td>
<td>-27.270</td>
<td>-23.917</td>
</tr>
<tr>
<td></td>
<td>(5.637)***</td>
<td>(6.584)***</td>
</tr>
<tr>
<td>$S_{t-3}$</td>
<td>-0.773</td>
<td>-0.704</td>
</tr>
<tr>
<td></td>
<td>(0.210)***</td>
<td>(0.214)***</td>
</tr>
<tr>
<td>$E_{t-2}$</td>
<td>19.935</td>
<td>17.098</td>
</tr>
<tr>
<td></td>
<td>(4.222)***</td>
<td>(4.991)***</td>
</tr>
<tr>
<td>$R_{t-1}$</td>
<td></td>
<td>1.205</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.703)***</td>
</tr>
</tbody>
</table>

Log likelihood: -11.204, -9.577
$R^2_{McFadden}$: 0.6952, 0.7395
RMSE: 0.178, 0.163
AIC: 28.409, 27.154
BIC: 36.771, 38.305
HQC: 31.805, 31.683

Note: The probit models are estimated over the entire sample period 1979Q1 – 2009Q3. *, *** denote respectively significance at 10% and 1% levels. Robust standard errors are given in parentheses and are computed using the Huber-White method (for more details, see Davidson and McKinnon, 2004, chapter 10).

Figure 2. Probability of Recession, In-Sample Forecasting
5 Out-of-Sample Prediction of the 2008 Recession

The in-sample analysis reveals quite good results in terms of forecasting French recessions, especially for the dynamic probit model. However, it is not sufficient to evaluate the predictive performance of the considered models. Out-of-sample predictability must also be confirmed. We begin this section describing the forecasting procedure used, which is fundamentally dynamic.

5.1 The Forecasting Method

The general problem is to predict a binary variable, denoted $y_t$, $h$ quarters ahead given information at time $t$. It is well-known that the minimum mean-square error predictor of $y_t$ based on information set $I_{t-h}$ is given by

$$E(y_t | I_{t-h}),$$

i.e. by the conditional mean of $y_t$. As our model defined by (2) and (3) is truly dynamic, the conditional expectation of $R_t$ becomes by the law of iterated expectations

$$E_{t-h}(R_t) = E_{t-h}[\Pr(R_t = 1 | I_{t-h})].$$

Evidently $E_{t-h}$ signifies conditional mean with respect to $I_{t-h}$.

Using our estimated model with the lagged recession indicator and formula (3), optimal forecasting made at time $t-h$ requires thus to compute

$$E_{t-h}(R_t) = E_{t-h}(\Phi(z_t)),$$

where $\Phi$ is the cumulative distribution function of a standard normal random variable and $z_t = \gamma_0 + \rho R_{t-1} + \gamma_1 S_{t-3} + \gamma_2 E_{t-2}$, with $S$ the interest rate spread and $E$ the spot exchange rate.

Prediction of $R_t$ can be conducted in two manners: directly or iteratively. (See Marcellino and al. (2006).) The method used is a variant of this second procedure. By nature, the considered model is here dynamic since the recession probability for a particular quarter $t$ requires as input the value of the recession indicator in $t-1$. To be as realistic as possible, the estimation is carried out up to a date for which the value of $R_t$ is known with “certainty”. The problem arises from the delay in the GDP’s publication and its potential revisions. That's why we choose the fourth quarter of 2005.
Moreover, the forecasts have the particularity to be *dynamic* in that they employ the “chain rule of forecasting”. This means that the probability of recession will be generated using the prior forecast instead of using the true value – 0 or 1 – for the binary indicator. By applying the law of iterations, one can also notice that the forecasts will principally depend on the longer history of the two financial variables. In this way, the procedure manage us to get round the problems in the GDP’s publication and finally, we make the forecast horizon equal to the minimum of \((k^*_1, k^*_2)\), namely 2 quarters in our application.

Unlike to the previous section, we need to separate the forecasting period from the estimation one. To the extent that we need enough data for obtaining satisfactory coefficient estimates, the estimation period should contain the two first recessions. Then, the forecasts could be made over the remaining period and so be applied to the 2008 recession. Further, we only focus on the out-of-sample performance of the dynamic model. The corresponding analysis will be constructed in three steps:

1. Estimate the dynamic probit model (7) over the restricted sample period 1979Q1 – 2005Q4, considering the optimal lag orders defined in the section 4.1.
2. Generate the recession probabilities over the forecasting period 2006Q1 – 2009Q3, using the coefficient estimates obtained in the first step.
3. Evaluate the out-of-sample fit by comparing the forecasts with the actual values of the binary recession indicator.

### 5.2 Out-of-Sample Results

Figure 3 illustrates the results of the out-of-sample procedure described above. The 2-quarter-ahead forecasts are compared with the realized values of the recession indicator across 2006Q1 – 2009Q3.

It can be seen that the model manages to predict the beginning of the latest recession as with the in-sample exercise. The predicted recession probability gradually increases during the year 2007 to reach almost 100% as the recession really began. This strong recession signal remains so high until the first quarter of 2009 before falling during the last two quarters.

These results can be put in connection with the evolution of the two financial predictors (see figures A1 and A2 in appendix A). From 2006, the spot exchange
rate clearly exhibits a strong appreciation of euro against US dollar. In parallel, the decline and inversion of the term structure of interest rates also yield some warnings about the future recession. At the beginning of the recession, long rates were always lower than short rates whereas the euro reached values without preceding (more than 1.50 US dollar). As theoretically expected, these two jointed effects account for the extended slowdown of real activity. The resultant probabilities lead thus to forecast a recession state up to 2009Q1.

According to the BBQ dating algorithm, the French economy was still in recession in 2009Q3. However, the out-of-sample forecasts would indicate a return to economic growth as far as the recession probability sharply drops under 10%. This can be justified by the sudden recovery of both the slope of the yield curve and the US dollar against euro (see figures A1 and A2). In comparison, the in-sample analysis was somewhat different. Indeed, the recession signal only fell to 40% making less likely the transition to an expansionary state.

Overall, the results confirm the out-of-sample performance of the dynamic probit model in predicting the 2008 recession despite the gap between the forecast and the binary indicator at the end of the sample period. Nevertheless, we must be careful in interpreting this discrepancy since the BBQ’s censoring rules do not allow us to locate turning points at the bounds of the series. In other words, the upturn in the French business cycle cannot occur at the time the recession probability declines. To date the end of the 2008 recession, we would need to extend the sample period but data on GDP were not available after the third quarter of 2009.
6 Conclusions

This paper has examined the usefulness of financial variables in forecasting French recessions over the period 1979 – 2009. Static and dynamic binary probit models have been employed with only two predictors – the yield curve spread and the EUR/USD exchange rate – so that the corresponding models remain parsimonious. To proceed, we have firstly established the French business cycle chronology by applying the non-parametric dating algorithm BBQ to the quarterly real GDP series. Then, in-sample and out-of-sample exercises have been carried out to evaluate the predictive performance of the probit models.

Three main results emerge from the in-sample analysis. First, both the term spread and the EUR/USD exchange rate are statistically significant predictors and have the theoretically expected effect about future French recessions. Second, the dynamic specification yields more accurate predictions than the static one in the sense that it allows reducing some spurious depression signals. Third, the lag order selection for the explanatory variables, which fundamentally determines the predictive horizon, is an important factor in the forecasting accuracy. Based on the 2008 recession, the out-of-sample exercise leads us to develop 2-quarter-ahead dynamic predictions, and it also provides an accurate detection of the crisis.

Finally, it would be interesting to extend future researches in several directions, for example, by including other countries in the context of panel data or other financial variables to make inter-country comparisons. Likewise, given that the recession indicator $R_t$ is a constructed binary time series future research should consider the “Harding-Pagan critics”: see Harding and Pagan (2009). However, tomorrow is another day…
REFERENCES


## Appendix A. Description of Data

<table>
<thead>
<tr>
<th>Series</th>
<th>Periodicity</th>
<th>Description</th>
<th>Sources</th>
</tr>
</thead>
<tbody>
<tr>
<td>$y_t$</td>
<td>Quarterly</td>
<td>Logarithm of real French GDP.</td>
<td>Bank of France</td>
</tr>
<tr>
<td></td>
<td>1979Q1 – 2009Q3</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R_t$</td>
<td>Quarterly</td>
<td>Recession indicator that takes the value one when the French economy is in recession and zero otherwise. This binary variable is constructed by the application of BBQ algorithm to $y_t$.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1979Q1 – 2009Q3</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$SPREAD_t$</td>
<td>Quarterly</td>
<td>10-year government bond yield minus 3-month PIBOR</td>
<td>Bank of France</td>
</tr>
<tr>
<td></td>
<td>1979Q1 – 2009Q3</td>
<td></td>
<td>via OECD’s website</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Monthly (quarterly) data are averages of daily rates (monthly figures).</td>
<td></td>
</tr>
<tr>
<td>$S_t$</td>
<td>Quarterly</td>
<td>EUR/USD spot exchange rate that expresses the price of one euro in terms of US dollars. Prior to 01/01/1999, the BIS uses the European component currencies of ECU, their quotation against USD and their fixed conversion against EUR. The EUR/USD exchange rate is finally calculated as a weighted average of these exchange rates against USD for the European Monetary System period.</td>
<td>BIS</td>
</tr>
<tr>
<td></td>
<td>1979Q1 – 2009Q3</td>
<td></td>
<td>via OECD’s website</td>
</tr>
</tbody>
</table>
Figure A.1. The Interest Rate Spread

Figure A.2. The EUR/USD Spot Exchange Rate