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Forecasting euro area recessions using time-varying binary response models for financial variables

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Abstract

Recent macroeconomic evolutions during the years 2008 and 2009 have pointed out the impact of financial markets on economic activity. In this paper, we propose to evaluate the ability of a set of financial variables to forecast recessions in the euro area by using a non-linear binary response model associated with information combination. Especially, we focus on a time-varying probit model whose parameters evolve according to a Markov chain. For various forecast horizons, we provide a readable and leading signal of recession by combining information according to two combining schemes over the sample 1970-2006. First we average recession probabilities and second we linearly combine variables through a dynamic factor model in order to estimate an innovative *factor-augmented probit* model. Out-of-sample results over the period 2007-2008 show that financial variables would have been helpful in predicting a recession signal as September 2007, that is around six months before the effective start of the 2008-2009 recession in the euro area.

Keywords: Macroeconomic forecasting, Business cycles, Turning points, Financial markets, Non-linear time series, Combining forecasts.

JEL codes: C53, E32, E44

Résumé

Les fluctuations macroéconomiques récentes des années 2008 et 2009 sont venues souligner l'impact des marchés financiers sur l'activité économique. Dans ce papier, on se propose d'évaluer la capacité d'un ensemble de variables financières à anticiper les récessions au sein de la zone euro, en utilisant un modèle non-linéaire à réponse binaire associé à une procédure de combinaison de l'information. En particulier, on s'intéresse à un modèle de type probit dont les paramètres évoluent au cours du temps selon une chaîne de Markov. Pour différents horizons de prévision, nous fournissons un signal de récession fiable et avancé sur la période 1970-2006 en combinant l'information de deux manières différentes. D'abord, nous calculons la moyenne des prévisions de récession obtenues à partir de chacune des variables, ensuite nous combinons les variables à l'aide d'un modèle à facteurs dynamiques. Ce dernier modèle de type *factor-augmented probit* constitue une innovation dans la littérature. Les résultats hors-échantillon sur la période 2007-2008 montrent que cet ensemble de variables financières aurait permis de fournir un signal de récession dès le mois de septembre 2007, soit environ six mois avant le début effectif de la récession de 2008-2009 en zone euro.

Mots clés: Prévision macroéconomique, Cycles économiques, Points de retournement, Marchés financiers, Séries chronologiques non-linéaires, Combinaison de prévision.

Codes JEL: C53, E32, E44

1 Introduction

The year 2008 has painfully recalled to the economic community that economic business cycles were still alive. In spite of the 'Great Moderation' theory argued by several research papers (see among others McConnel and Perez-Quiros, 2000, or Giannone et al., 2008), a severe recession has affected simultaneously most of the industrialized countries in the following of the US sub-prime credit crisis. The National Bureau of Economic Research (NBER) Dating Committee has announced in December 2008 (NBER, 2008) that a 'peak in the economic activity occured in the U.S. economy in December 2007'. In the same way, in March 2009, the Centre for Economic Policy Research (CEPR) has also determined a peak in the euro area economic activity during the first quarter of 2008 (CEPR, 2009). Ex-post recession dating is an essential exercise for business cycle analysis but forecasting recession in real-time is a more challenging issue for macroeconomic forecasters and policy-makers. In this paper our aim is to put forward a new tool enabling to anticipate the probability of economic recessions in the euro area by using financial markets information.

According to the very specific nature of the 2008 recession, mainly due to the financial sector, a crucial issue for practitioners is to know whether a monitoring of some financial data would have been allowed to forecast this recession. Several empirical studies have shown evidence that the information conveyed by financial market variables is a very powerful tool in predicting macroeconomic time series, especially output (we refer for example to Stock and Watson, 2003, Estrella, Rodrigues and Schich, 2003, Giacomini and Rossi, 2006, King et al. 2007, and the references therein). Among all the considered variables, it turns out that most reliable variable is the spread between long-term interest rates (generally 10 years) and short-term interest rates (generally 3 months). A wide strand of the empirical literature focuses on the ability of the term spread to forecast recessions, we refer among others to the papers of Mishkin (1989), Bernanke (1990), Estrella and Hardouvelis (1991), Plosser and Rouwenhorst (1994), Estrella and Mishkin (1997, 98), Bernard and Gerlach (1998), Duarte, Venetis and Paya (2005), Moneta (2005), Chauvet and Potter (2002, 2005), Kauppi and Saikkonen (2008), Nyberg (2009) or Rudebusch and Williams (2009). Other variables like stock prices (Estrella and Mishkin, 1998, de Bondt, 2009) or oil prices (Hamilton, 2003) have also been proved to contain predictive information of future economic fluctuations. In this paper, we consider a new dataset of various financial markets variables that are available over a large sample size, since early seventies, and that are potentially useful to anticipate recessions in the euro area. This dataset includes for example various term spreads, stock markets variables and commodities prices (see Section 3 for details).

Regarding the econometric methodology, our aim is to get an estimate of the probability of being in recession few months ahead. In this respect, parametric modelling is generally used to assess this probability. Among all available parametric models, binary response models, such as logit and probit, have widely proved their ability to forecast business cycles. For recent empirical applications, we refer for example to Chauvet and Potter (2002, 2005), Estrella, Rodrigues and Schich (2003), Kauppi and Saikkonen (2008), Nyberg (2009) or Rudebusch and Williams (2009). An important aspect of the use of binary response models in business cycle analysis, is that the phases of the cycle have to be known *a priori*, before the analysis. Thus, the practitioner has to identify the turning points of the cycle along the sample path, that is the dates where there is a switch between phases. Generally, the chosen dates are those stemming from a reference dating. When dealing with the U.S. business cycle, the reference chronology is given by the NBER. When dealing with the euro area aggregated economic cycles, the CEPR updates a turning point chronology and Eurostat provides with a dating chronology for both business and growth cycles (see Mazzi and Savio, 2007, or Anas et al. 2007). A review of the existing turning point chronologies for the euro area is available in Anas at al. (2008) and we refer also to Ferrara (2009) for chronologies of various types of economic cycles in the zone.

In spite of their widely acknowledged predictive ability, financial time series are not often integrated in short-term macroeconomic forecasting models. This is mainly due to two stylised facts, namely high volatility and unstability overtime. To take those two elements into account, various extensions of parametric models have been put forward in the literature. For example, regarding binary response models, Chauvet and Potter (2002, 2005) allow structural breaks to reduce unstability and Kauppi and Saikkonen (2008) use a dynamic model that integrates past values of both dependent variables and conditional probabilities of being in recession in order to smooth the estimated signal. An interesting generalisation has been put forward by Dueker (1997, 2002) who allows time-varying parameters that evolve according to a Markov chain in order to take endogeneous breaks into account. Keeping in mind that our tool has to be used for real-time analysis, we priviledge this latter specification in our approach. Indeed, the estimation procedure put forward by Chauvet and Potter (2002, 2005) involves a complex algorithm while the model introduced by Kauppi and Saikkonen (2008) cannot directly be used in real-time because the dependent variable is obviously unknown. Last, another useful way to reduce volatility is information combination. For example, King et al. (2007) improve accuracy of recession forecasts by using a bayesian average of probabilities. In this paper, we propose to compare two combining schemes. First we average predicted recession probabilities stemming from simple probit models applied to each variable and second we linearly combine variables through a dynamic factor model in order to estimate a factor-augmented probit model. This latter *factor-augmented probit* approach is innovative in the literature.

To sum up, in this paper we evaluate the ability of a new dataset of financial variables to predict business cycle turning points in the aggregate euro area, for various forecast horizons ranging from one to twelve months. Historical financial variables from early seventies are used for the first time in this framework. We focus on the time-varying probit model introduced by Dueker (1997, 2002), allowing estimated probabilities of recessions few months ahead. We provide a readable and leading signal of recession by combining information according to two combining schemes over the sample 1970-2006. Especially, we propose an innovative *factor-augmented probit*. In-sample results show that this approach enables to correctly replicate past recessions from 1970 to 2006 and out-of-sample results over the period 2007-2008 suggest that financial variables would have been helpful in anticipating a recession signal in the euro area as end of 2007.

2 Binary response modelling

We assume that we observe the values of a binary variable $(r_t)_t$ that takes for value 1 when the economy is in recession at date t and 0 otherwise. Binary response models rely on the assumption that the values of the binary dependent variable $(r_t)_t$, stem from a latent continuous variable, denoted $(y_t)_t$, defined by the following linear equation, for all t,:

$$y_t = \alpha + \beta' x_{t-k} + \varepsilon_t, \tag{1}$$

where $x_{t-k} = (x^1_{t-k}, \ldots, x^n_{t-k})'$ is a n-vector of explanatory variables, $k \geq 0$ is a lag, $\beta = (\beta^1, \ldots, \beta^n)'$ is the n-vector parameter and $(\varepsilon_t)_t$ is the error term supposed to follow a strong white noise process with finite variance σ^2_ε. The distribution of $(\varepsilon_t)_t$ is discussed below. Most of the time, in empirical applications, n is taken such that $n = 1$ and the explanatory variable is delayed with a given lag $k \geq 1$ that corresponds to the forecast horizon.

The observed binary variable $(r_t)_t$ is linked to the latent variable $(y_t)_t$ by the following relationship:

$$r_t = \begin{cases} 1 & \text{if } y_t \leq 0, \\ 0 & \text{if } y_t > 0 \end{cases} \tag{2}$$

For each date t, it can be easily proved that the conditional probability that an economic recession occurs, conditionally to Ω_t, the whole information set available at date t, is given by the simple model :

$$P(r_t = 1|\Omega_t) = P(r_t = 1|x_{t-k}) = F(-\alpha - \beta' x_{t-k}), \tag{3}$$

where $F(.)$ is the cumulative density function of the variable $(\varepsilon_t)_t$. For example, the probit model is defined by assuming that the error term $(\varepsilon_t)_t$ is Gaussian, that is $F(.)$ is the cumulative density function (cdf) of the standard Gaussian distribution. The shape of the function $F(.)$ allows to discriminate between various binary response models. For example, the well known logit model uses for $F(.)$ the logistic function. Both logistic and cdf standard Gaussian functions allow to plug the quantitative information contained in $(x_{t-k})_t$ into the interval $[0, 1]$. The logistic function appears to be smoother than the cdf standard Gaussian in the sense that the transition from 0 to 1 takes more time. In other words, the cdf standard Gaussian is closer to the indicator function $1_{(z>0)}$ describing a discrete transition from 0 to 1. In this paper, we focus only on the probit version of the models.

Initially, binary response models have been developed to describe independent data. When dealing with time series, it is clear that this assumption is often broken due to the inherent nature of the data. In this respect, autocorrelation in the error term has to be taken into account in modelling. For example, several lagged values of the explanatory variable may be included into the model as well as lagged dependent binary variable $(r_{t-k})_t$. Thus, a dynamic version of the model could be described by the following equation:

$$P(r_t = 1|\Omega_t) = F(-\alpha - \sum_{j=k}^{q} \beta_j' x_{t-j} - \sum_{j=k}^{p} \delta_j' r_{t-j}), \tag{4}$$

with $q \geq k$ and $p \geq k$.

To introduce more flexibility into the model and to take the unstability of financial variables into account, we assume that the parameters of equation (1) evolve through time. In this respect, as in Dueker (1997, 2002), we assume that the parameters of the probit model are time-varying and evolve according to a first order Markov chain. This specification constitutes an attractive alternative to equation (4) to account for autocorrelation effects in binary-dependent models. We assume thus the existence of an unobserved variable $(s_t)_t$ that follows a two-state Markov chain, taking the values 0 or 1, such that the transition probabilities are given by:

$$P(s_t = 0|s_{t-1} = 0) = p_{00}, P(s_t = 1|s_{t-1} = 1) = p_{11}. \tag{5}$$

Thus, the latent continuous variable is such that:

$$y_t = \alpha(s_t) + \beta(s_t)' x_{t-k} + \varepsilon_t, \tag{6}$$

and y_t depends on both s_t and the lagged explanatory variable x_{t-k}. This approach enables to include some kind of persistence in modelling through the evolution of $(s_t)_t$. At time t, we note Ω_t the available information set such that

$$\Omega_t = (s_t, r_{t-1}, r_{t-2}, \ldots, X_{t-k}, X_{t-k-1}, \ldots).$$

Thus, the probability that a recession occurs at time t conditionally on Ω_t is given by:

$$P(r_t = 1|\Omega_t) = P(y_t \leq 0|\Omega_t) = \int_{-\infty}^{0} f_{y_t|\Omega_t}(u) du, \tag{7}$$

where

$$f_{y_t|\Omega_t} = f(y_t|\Omega_t) = \sum_{i=0}^{1} f(y_t|s_t = i, \Omega_{t-1}) P(s_t = i|\Omega_{t-1}). \tag{8}$$

By using the two previous equations (7) and (8), as well as the expression of the conditional distribution of y_t, it can be proved that the conditional recession probability can be rewritten as:

$$\begin{aligned} P(r_t = 1|\Omega_t) &= F(-\alpha(0) - \beta'(0) x_{t-k}) P(s_t = 0|\Omega_{t-1}) \\ &+ F(-\alpha(1) - \beta'(1) x_{t-k}) P(s_t = 1|\Omega_{t-1}) \end{aligned} \tag{9}$$

Parameter estimation is carried out using maximum likelihood estimation (MLE) methods. To estimate the time-varying probit model (TV-probit hereafter) we implement the methodology described in Hamilton (1994) for markov-Switching models, and we maximize the following log-likelihood function:

$$L(\theta) = \sum_{t=1}^{T} r_t \log[P(r_t = 1|\Omega_t)] + (1 - r_t) \log[P(r_t = 0|\Omega_t)], \tag{10}$$

where $P(r_t = 1|\Omega_t)$ is given in equation (9) and $P(r_t = 0|\Omega_t) = 1 - P(r_t = 1|\Omega_t)$.

The transition probabilities p_{ij} given in equation (5) determine the unconditional probability that the process will be in regime 0 at any given date, such that:

$$P(s_t = 0) = \frac{1 - p_{11}}{2 - p_{11} - p_{00}}, \tag{11}$$

and $P(s_t = 1) = 1 - P(s_t = 0)$.

As the states $s_t = 0$ and $s_t = 1$ are unobserved, we need to estimate the probabilities $P(s_t = 1|\Omega_{t-1})$ and $P(s_t = 0|\Omega_{t-1})$ described in equation (9). We are going to implement the algorithm proposed in Hamilton (1994) based on the iteration of prediction and update equations. Assume that for a certain date $t-1$, $P(s_{t-1} = 1|\Omega_{t-2})$ and $P(s_{t-1} = 0|\Omega_{t-2})$ are known. By direct application of the Bayes formula, the following equation enables to update the information set Ω_{t-2}, for $i = 0, 1$:

$$P(s_{t-1} = i|\Omega_{t-1}) = \frac{P(r_{t-1}|s_{t-1} = i, \Omega_{t-2}) \cdot P(s_{t-1} = i|\Omega_{t-2})}{\sum_{i=0}^{1} P(r_{t-1}|s_{t-1} = i, \Omega_{t-2}) \cdot P(s_{t-1} = i|\Omega_{t-2})}. \tag{12}$$

Then, by using the transition probabilities defined in (5) we get the following equation that allows to predict the regime $s_t = i$ for $i = 1, 2$:

$$P(s_t = i|\Omega_{t-1}) = P(s_{t-1} = 1|\Omega_{t-1}) \cdot p_{1i} + P(s_{t-1} = 0|\Omega_{t-1}) \cdot p_{0i}. \tag{13}$$

Using the starting values of $P(s_1 = 1|\Omega_1)$ (resp. $P(s_1 = 0|\Omega_1)$) as being the ergodic proababilities $P(s_1 = 1)$ (resp. $P(s_1 = 0)$), the Hamilton algorithm based on the iteration of equations (13) and (12) can be initialized. The optimization program is based on the Nelder-Mead approach and has been implemented using the R software. Initial values are needed to launch the optimization algorithm. We find those initial values by estimating the parameters from the simple model given in equation (3), namely $\hat{\alpha}$ and $\hat{\beta}$. This way, we set $\alpha^{(0)}(0) = \alpha^{(0)}(1) = \hat{\alpha}$ and $\beta^{(0)}(0) = \beta^{(0)}(1) = \hat{\beta}$ to start the algorithm and we choose the initial transition probabilities to be $p_{00}^{(0)} = p_{11}^{(0)} = 0.9$. We then iterate the optimization algorithm in order to reach parameter convergence.

3 In-sample analysis for financial variables

In this section, we evaluate in-sample properties of a set of financial variables in their ability to anticipate the euro area business cycle phases from January 1974 to December 2006.

Concerning the benchmark dating chronology, we use the business cycle turning point chronology proposed by Anas et al. (2007). They provide both a quarterly chronology based on GDP and a monthly chronology based on IPI. As we need a monthly reference for our exercice, we choose the IPI chronology except for the year 2001 in which for the first time in euro area countries an industrial recession occured without a global recession. Since 1974, we retain thus four recession periods until 2006 from peak to trough: March 1974 - March 1975, January 1980 - December 1980, September 1981 - December 1982 and February 1992 - February 1993.

Data selection process has been carried out under several constraints. When dealing with recession analysis, we face the issue of a narrow learning set. That is, from early seventies, the euro area has only experienced four recessions. Thus, we need long historical series. Unfortunately, the volume of recent financial data is incredibily huge, but getting historical financial data is not a easy task. Another constraint relates to the frequency of the data insofar as we aim at dealing with monthly time series. One of the innovation of this paper is that we test several new variables from financial markets in euro area with relatively long sample (generally starting in the 1970's). Here thirteen various variables are considered in their ability to anticipate business cycle fluctuations.

The first subset of variables includes different yields. First of all, we test the yield curve slope for the euro area. In this zone, Germany is often used as a benchmark and hence we use the 10 years minus 3 months (10y-3m) spread in the German market. Then, we test several corporate spreads: two stem from the German market (the spread between the corporate rate and the 1-year government bond rate and the spread between the corporate rate and the 3-month interbank rate), and one from the US market (the spread between the corporate rate and the 1-year government bond rate). The last spread is a measure of the liquidity on the market, referred to as liquidity spread, and consists in the spread between the 3-month interbank rate and the 1-year government bond rate on the German market. The contribution of this kind of variables, especially the 10 years - 3 months term spread, has been largely well discuted among several papers as noted in the introduction. However, the other variables that we used are innovative in this framework.

The second subset of variables embraces three variables from the euro area stock market to test their forward-looking nature over the real economy. First the stock index, then the dividend yield, and finally the Price / Earning ratio (PER). From different valuation theories, as for example the discounted dividend models theory, the stock index potentially includes information about the future shape of the economy. The dividend yield on a company stock is the company's annual dividend payments divided by its market cap. Even if the forward-looking nature of the dividend yield is not well established, it can be considered by some investors as indicative of the overvaluation (or undervaluation) of the market. The PER is a measure of the price paid for a share relative to the annual net income or profit earned by the firm per share. The PER of a stock index implicitly incorporates the perceived risk of future earnings.

The third subset of variables is composed of three variables from the commodities market, namely the Commodity Research Bureau (CRB) price index, the oil spot price index and the gold price index. Evidence of relationships between oil prices and the macroeconomy has been already pointed out in the literature (see for example Hamilton, 2003), thus we test its effect on the euro area business cycle. Gold price is also considered in the sense that gold is generally used as a safe haven against economic crises.

Finally, two different individual variables from financial markets are also used in this paper: the US default rate and the monetary aggregate (M1 seasonally adjusted). Note also that other variables, such as the Euro Trade Weighted Index, have been preliminary tested, but we have only retained the most meaningful variables under the condition that they are available over the whole sample. Data and sources are presented in Table 3.

For each considered variable $(x_t^j)_t$, $j = 1, \ldots, 13$, we first determine whether the variable is stationary or not by using standard tests. When the variable is stationary, we use it without any transformation (i.e. in level), otherwise we transform it by taking the growth rate over 6 months. For each variable, transformed or not, we then consider several forecast horizons of h months, such that $h \in \{1, 3, 6, 9, 12\}$. This horizon h is put in place of lag k in equations (3) and (9). For the whole sample period from 1974 to 2006, we estimate parameter by MLE, as described in the previous section. Thus, for each variable $(x_t^j)_t$, we get in output the estimated probability of being in recession h-steps ahead, denoted $\hat{P}^j(r_{t+h} = 1|\Omega_t, \hat{\theta})$.

To assess the ability of each variable $(x_t^j)_t$ to anticipate business cycle phases, we use a general goodness-of-fit criterion for each forecast horizon h and we choose the quadratic probability score (QPS) given by:

$$QPS(j, h) = \frac{1}{T} \sum_{t=1}^{T-h} (r_{t+h} - \hat{P}^j(r_{t+h} = 1|\Omega_t, \hat{\theta}))^2 \tag{14}$$

For example, Figure 1 presents the probabilities of being in recession one-step ahead stemming from both simple probit (top) and TV-probit (bottom) models applied to the spread between the 3-months inter-bank rate and the 1-year government bond. This latter probability appears to be clearly smoother than the previous one and provides a better goodness-of-fit, the QPS criterion falling from 0.96 to 0.64 (see Table 5). The filtered state probability is presented in Figure 2. We observe that the underlying states correspond to the recession phases, meaning that coefficients of the model differ during recessions.[1] Another example is proposed in Figure 3 where the results for the dividend yield series are plotted (for $h = 1$). We observe that the TV-probit model enables to take the 1992-93 recession into account, which improves the goodness of fit (the QPS drops from 0.077 to 0.060). In fact, when looking at Figure 4 we note that the state probability increases to 0.75 during this specific recession and takes value 0 otherwise. In this example, the TV-probit model captures the switch in parameters occuring only at this period, underlining thus the great flexibility of the model.

[1]For parcimony reasons, parameter estimates for both simple probit and TV-probit models, for all forecast horizons, are not presented here but are available upon request.

In terms of QPS, it turns out that the most relevant variable is the 10-years minus 3-months term spread, especially for $h \geq 3$ (see Table 5). The two corporate spreads convey also useful predictive information for an horizon between 6 and 12 months. Variables reflecting the euro area stock market give interesting results, especially the Dividend Yield and the PER, for $h = 1$ and $h = 3$, which provide valuable information about the three first recessions (even if there is some noise between them), while the stock index series seems to contain less useful information. The other variables provide sporadic information: Either they detect only one or two recessions among the four ones in the sample or they provide weak recession signals and few false signals, especially variables M1 and US default rate.

For variables such as Dividend yield, PER, Spread corporate rate - interbank rate, US credit spread, CRB price index, Oil price index, the QPS is always clearly lower with the TV-probit specification. For variables such as the yield curve slope, monetary aggregate M1, Euro Trade Weighted, the difference is rather small. When the difference is high, this corresponds to cases for which the TV-probit model enables to detect recessions that the simple model is not able to detect. When the TV-probit model applied to a given varaible does not enable to reduce the QPS criterion, it means that this variable contains a single regime and thus the TV-probit reduces to a simple probit model. The improvements from TV-probit specification always match with changes in regimes. We have noticed that recessions do not necessarily match with changes in regime, but when the TV-probit identifies a recession not estimated by the simple model, it always matches with a change in regime. For instance, regarding the dividend yield variable, the TV-probit model detects the 1992-93 recession whereas the simple model does not (Figure 3).

4 Combining information

From the previous analysis, it turns out that variables useful to predict a given recession are not necessarily useful to anticipate all the recessions. Thus we decide to improve the ability of our tool to anticipate recessions, from 1970 to 2006, by combining information. In this respect we propose two combining schemes, namely, first, by combining probabilities and, second, by combining variables through a dynamic factor model.

4.1 Combining probabilities through averaging

It is well known that combining probabilities of recession estimated from various models or various variables can improve the results obtained from a single predictor. For example, Anas and Ferrara (2004) and Anas, Billio, Ferrara and Mazzi (2008) have developed recession indicators for real-time detection based on a weighted average of recession probabilities. In the same framework, King, Levin and Perli (2007) conclude also that a bayesian averaging of recession probabilities improve the accuracy of prediction in comparison with simple averaging.

In this respect, we propose a simple tool based on the average of all probabilities, for each forecast horizon h, defined in the following way:

$$\hat{\hat{P}}(r_{t+h} = 1|\Omega_t) = \frac{1}{n}\sum_{j=1}^{n} \hat{P}^j(r_{t+h} = 1|\Omega_t), \tag{15}$$

where $\hat{P}^j(r_{t+h} = 1|\Omega_t)$ stems from equation (3) or (9) and $n = 13$ in our application. For example, results for $h = 3$ are presented in Figure 5 for both simple probit (top) and TV-probit (bottom) models. From both graphs, we observe that this tool tends to increase for each recession but does not cross the natural threshold value of 0.50. Combining probabilities from TV-probit models gives a noiseless signal and provides greater probability values, allowing thus an easier identification of recession phases. From Table 5, we observe that combining probabilities enables to improve the outcomes in QPS terms by comparison with univariate estimated simple probit models.It is noteworthy that the lowest QPS is reached for an horizon of 9 months, that can be seen as the average lead over the business cycle.

Note also that we have also tried various weighting schemes, but uniform weighting provides with the best results in the QPS sense. However, more sophisticated statistical averaging methods could be used to improve the results.

4.2 Combining variables through a dynamic factor model

Another alternative to combine information is to linearly combine variables into a small number of factors before putting them into a probit model. We define this approach as *factor-augmented probit* modelling. Recently, many research papers have focused on the issue of dimension reduction of large scale databases. For example, Stock and Watson (2002) and Forni et al. (2004) have put forward dynamic factor models in order to summarize macroeconomic information. Such approaches have been extensively used in several directions, especially for macroeconomic forecasting; we refer for example to Stock and Watson (2006), Angelini et al. (2008), Marcellino and Schumacher (2008) or Barhoumi, Darné and Ferrara (2009) for applications, as well as to Eickmeier and Ziegler (2008) for a review.

In the factor model framework, variables $(x_t)_t$, are represented as the sum of two mutually orthogonal unobservable components: the common component χ_t and the idiosyncratic component ξ_t. For a given t, $t = 1, \ldots, T$, the factor model is defined by:

$$x_t = \Lambda F_t + \xi_{t,} \tag{16}$$

where $x_t = (x_t^1, \ldots, x_t^n)'$ is a vector of n stationary time series and it is assumed that the series have zero mean and semi-definite positive covariance matrix, Λ is the loading matrix, the common component $\chi_t = \Lambda F_t$ is driven by a small number r of factors F_t common to all the variables in the model such that $F_t = (F_t^1, ...F_t^r)'$, and $\xi_t = (\xi_t^1, ..., \xi_t^n)'$ is a vector of n idiosyncratic mutually uncorrelated components, driven by variable-specific shocks.

In this paper, we implement the estimation method proposed by Stock and Watson (2002) that uses static principal component analysis to estimate the unobserved factor F_t and we assume that $r = 3$[2]. The first three factors account for around 60% of the total variance, which is reasonable in such empirical studies. It is noteworthy that the first factor is described by term spreads variables, while the second one represents stock markets variables and the third one is strongly correlated to commodities.

After having estimated the factors F_t, we use it as explanatory variable in the models defined by equations (3) and (9) in order to get a probability of being in recession h-step ahead. Parameter estimates for both models, for all forecast horizons, are presented in Table 6. We note first that absolute values of parameters $\hat{\beta}_j$ are quite close from each other for $h = 1$, but when the horizon h increases the first factor, mainly explained by term spreads, becomes more and more important. This means that for the longest horizons, namely as $h \geq 6$, the information conveyed by the interest rate spreads is the most valuable. Especially, for $h = 9$ the parameter estimate of the first factor, $\hat{\beta}_1$, is largely greater than $\hat{\beta}_2$ and $\hat{\beta}_3$, underlying the major importance of this factor at this horizon. This result is consistent with the outcomes from the univariate analysis presented in the previous section. The TV-probit model shows clearly evidence of a different pattern according to the regime, in terms of estimates values. For each horizon, at least one of the two transition probabilities is close to one, implying that one of the regime is always highly persistent. Estimated probabilities from both simple and TV factor-augmented probit approaches are presented in Figure 6, for $h = 3$. We observe that predicted recession probabilities have been increased to a large extend pointing out the usefulness of this approach when comparing with the previous combining scheme. When comparing with results obtained for each individual variable from the QPS point of view (Table 5), we note a clear improvement using this approach for all horizons. Is is also noteworthy that factor-augmented TV-probit models possess a better goodness-of-fit for each horizon h in comparison with factor-augmented simple probit ones. The simple factor-augmented probit approach reaches its minimal QPS for $h = 9$, as for the previous combining scheme. This average lead of nine months is consistent with the empirical literature on financial variables. Regarding the TV factor-augmented probit, the estimated lead of financial variables is smaller, close to $h = 3$.

4.3 Decision rule

It is always useful for policy-makers to get a decision rule instead of having a single probability to interpret. Therefore a decision rule has to be set up in order to send accurate signals of upcoming recessions. In this respect, we estimate a threshold over which a signal of an upcoming recession will be given and under which the economy is supposed to be in expansion. To achieve this objective, we estimate this threshold using a grid-search procedure that maximizes the corrected contingency coefficient put forward by Artis, Krolzig and Toro (2004) and based on the Pearson's goodness-of-fit criterion (see Appendix for

[2]The inclusion of a greater number of factor into the logit models has not been found statistically significant

details).

Estimated thresholds are given in Table 1 for each forecast horizon h and for each combining scheme. For example, when using the average of all probabilities estimated through simple probit models (equation (15)), the critical threshold stands at 0.17 for $h = 1$ and $h = 12$ and at 0.18 for $h = 3, 6, 9$. The corresponding estimated critical thresholds are almost every time higher when using the average of all probabilities estimated through TV-probit models, implying thus a more readable signal. At the same time, we note an increase of the contingency coefficient values indicating better goodness of fit outcomes. When using the factor-augmented models, estimation of the simple probit model leads to slightly higher critical thresholds (except for $h = 6$) than those obtained with the previous combining scheme. When we implement a TV-probit model, as expected, critical thresholds tend to rise due to the strong readability of the signal. For example, the critical value stands at 0.51 for $h = 1$, close to the natural value of 0.50. But it is noteworthy that the contigency coefficients have not been systematically improved, leading thus to the conclusion that with this *ad hoc* specific rule, it is not necessary to get strong estimated probabilities of recession to send a clear signal.

5 Out-of-sample analysis

The objective of this section is to evaluate the ability of the previous apporaches to detect the occurence of the last recession in the euro area that has started during the first quarter of 2008 (CEPR, 2009). In this respect, we take the previous models estimated over the period 1974-2006 and we use them with data from January 2007 to December 2008. Thus, for each month t, from January 2007 to December 2008, we estimate the probability of being in recession h months ahead, $\hat{P}(r_{t+h} = 1|\Omega_t, \hat{\theta})$, according to the two combining schemes presented in section 4. As, obviously, $(r_t)_t$ is unknown over the forecasting period, it is not possible to re-estimate the models as new data are known. The solution that we use is to compute static forecasts in the sense that estimates are kept fixed over the forecasting period. Note however, that new factor estimates are computed with each new data. Last, for each forecast horizon h, we apply the decision rule involving the critical thresholds estimated previously in Table 1 in order to send a signal of recession

Horizon	Averaging probabilities				Factor-augmented models			
	simple probit		TV-probit		simple probit		TV-probit	
	Threshold	CC_{corr}	Threshold	CC_{corr}	Threshold	CC_{corr}	Threshold	CC_{corr}
$h = 1$	0.17	81%	0.20	87%	0.22	80%	051	91%
$h = 3$	0.18	87%	0.24	91%	0.21	81%	0.35	90%
$h = 6$	0.18	84%	0.19	88%	0.16	82%	0.25	84%
$h = 9$	0.18	84%	0.18	86%	0.19	82%	0.25	89%
$h = 12$	0.17	75%	0.23	81%	0.20	71%	0.18	78%

Table 1: Estimated critical thresholds for the decision rule and corresponding corrected contingency coefficients

or expansion h months ahead.

Out-of-sample forecasting results obtained with the first combining scheme, that is when averaging all probabilities, are presented in Figure 7 for simple probit models and in Figure 8 for TV-probit models. Overall, the use of TV-probit models enables to increase slightly the forecast probabilities, but the shape of each predicted probability remains the same. Note that the natural threshold of 0.50 has not been crossed. When using the critical values estimated before, the timing of the signal is given in Table 2. The striking feature is that, by using this decision rule, we would have been able to send a signal of recession in June 2008 with the simple probit model, while the use of TV-probit models would have led to send a first signal as February 2008.

Out-of-sample forecasting results obtained with the second combining scheme, that is when estimating factor-augmented models, are presented in Figure 9 for simple probit models and in Figure 10 for TV-probit models. Results obtained using the simple probit models are striking in the sense that the models provide very high probabilities, close to one for short horizons ($h = 1$ and $h = 3$). Those results appear also meaningful because the probabilities tend to decrease progressively when the horizon increases. By using the decision rule, with the estimated critical thresholds, we get that a persistent signal of recession could have been sent as September 2007 with a forecast horizon of nine months, indicating thus a recession starting in June 2008. It is noteworthy that this lead of nine months matches with the average lead of the financial variables estimated in the previous section. On the contrary, results obtained with TV-probit models are less clear-cut. Indeed, probabilities for each forecast horizon are not consistent and are strongly volatile, especially for $h = 3$ and $h = 9$. By using the decision rule, we get that a signal of recession could have been sent with the first data of the forecasting period (in January 2007) for $h = 12$. This signal is specifically leading but has to be considered with caution because of the volatile results obtained with this approach for forecasting purposes. We point out here the discrepancy that could occur between in-sample and out-of-samle results, as noted for example by Estrella and Mishkin (1998) in the same framework.

It should be stressed that the recession signals obtained with our approach would have been really leading in real-time. Recall that the CEPR announcement was released at the end of March 2009. Moreover, when using the often quoted rule of thumb saying that an economy falls into recession if two consecutive quarters of GDP growth are negative, we

	Averaging probabilities				
	$h = 1$	$h = 3$	$h = 6$	$h = 9$	$h = 12$
Basic probit	Jun. 2008	Jun. 2008	Jun. 2008	Sep. 2008	Oct. 2008
TV-probit	Jun. 2008	Jun. 2008	Feb. 2008	Feb. 2008	Oct. 2008
	Factor-augmented models				
	$h = 1$	$h = 3$	$h = 6$	$h = 9$	$h = 12$
Basic probit	Jun. 2008	Jun. 2008	Mar. 2008	Sep. 2007	Dec. 2007
TV-probit	Fev. 2008	Fev. 2008	Sep. 2008	Feb. 2008	Jan. 2007

Table 2: Timing of the signals using estimated critical thresholds

would have get a signal of recession the 14th November of 2008 when the flash estimate for Q3 2008 was released by Eurostat. In this respect, the tools that we have put forward enable to send early signals of recession in real-time.

6 Conclusions

In this paper, we propose to evaluate the ability of a set of financial variables to detect in advance business cycle turning points in the euro area by using non-linear binary response models. Especially, we focus on the time-varying probit model introduced by Dueker (1997, 2002) whose parameters evolve accroding to a Markov chain. We empirically show that financial market variables present leading properties and are useful to predict recessions in the euro area over the period 1974-2006. We have also pointed out that time-varying probit models associated with an information combining scheme, either by combining recession probabilities or by estimating innovative *factor-augmented probit* models, clearly improve in-sample fitting over this period. Concerning the last 2008-2009 recession, an out-of-sample experience from January 2007 to December 2008 shows that by using a *factor-augmented probit* model, we would have been able to anticipate the recession around six months before the effective date of the start. This approach can be easily carried out in real-time for monthly assessment and can be thus of great interest to macroeconomic forecasters and policy-makers.

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Appendix

Table 3: Data description

Predictor	**Availability date**	**Transformation**	**Source**
EA dividend yield	Jan. 1973	in level	Datastream
EA P/E ratio	Jan. 1973	in level	Datastream
EA stock index	Jan. 1973	growth rate over 6 months	Datastream
German spread: 10y gov. bond rate - 3mth interbak rate	Sept. 1972	in level	Bundesbank
German spread: 3mth interbank rate - 1y gov bond rate	Sept. 1972	in level	Bundesbank
German spread: corporate rate - 1y gov bond rate	Sept. 1972	in level	Bundesbank
German spread: corporate rate - 3mth interbank rate	Jan. 1970	in level	Bundesbank
US spread: corporate BAA rate - 1y gov bond rate	Jan. 1970	in level	US treasury and Moody's
US default rate	Jan. 1970	differences over 6 months	Moody's
CRB spot index	Jan. 1970	growth rate over 6 months	Commodity Research Bureau
Oil spot price	Jan. 1970	growth rate over 6 months	Bloomberg
Gold price	Jan. 1970	growth rate over 6 months	gold Bullion LBM
EA M1 sa	Jan. 1970	growth rate over 6 months	OCDE

Contigency coefficient
The Pearson's goodness-of-fit test tests the null hypothesis of independence of two binaries time series. Hence this method need to tranform the estimated probabilities time series of recession into a binary time series of recession using a threshold: when the probability is above the threshold it takes the value 1 and 0 otherwise. Under the null hypothesis of independence, the Pearson statistic $\hat{\chi}^2$ follows a chi-square distribution with 1 degree of freedom (for a 2×2 table) and is given by:

$$\hat{\chi}^2 = \sum_{i=0}^{1} \sum_{j=0}^{1} \frac{(n_{ij} - (n_{i.}n_{.j}/N))^2}{(n_{i.}n_{.j}/N)}, \tag{17}$$

where the n_{ij} are described in Table 4. The main drawback of this test comes from the nature of the business cycle: there is - fortunately ! - very few recessions implying thus that the expansion regime is extremely persistent. This strong autocorrelation of the binary variable leads to a strong rejection of the null hypothesis. Note that if we assume that the null hypothesis of independence is rejected, the greater the threshold is, the better the smoothed-probabilities fits the dating chronology.

Table 4: Contingency table

		Probability j		
		Expansion	Recession	Subtotal
Datation i	Expansion	n_{00}	n_{01}	$n_{0.}$
	Recession	n_{10}	n_{11}	$n_{1.}$
	Subtotal	$n_{.0}$	$n_{.1}$	N

The $\hat{\chi}^2$ statistics given in equation 17 allows to compute the Pearson's contingency coefficient, which is for binary data the equivalent to the conventional correlation coefficient for continuous data. For a finite dimension contingency table, the maximal attainable value is determined by the dimension of the table. For a 2×2 table, this maximal value is $\sqrt{0.5}$. Thus, to obtain a statistic which lies in the range 0-100, we use the corrected contingency coefficient, CC_{corr}, as in Artis, Krolzig and Toro (2004), given by:

$$CC_{corr} = \frac{CC}{\sqrt{0.5}} \times 100, \tag{18}$$

where:

$$CC = \sqrt{\frac{\hat{\chi}^2}{N + \hat{\chi}^2}} \tag{19}$$

Variables	$h=1$		$h=3$		$h=6$		$h=9$		$h=12$	
	Simple	TV	Simple	TV	Simple	TV	Simple	TV	Simple	TV
Dividend Yield	0.077	0.060	0.081	0.080	0.088	0.094	0.090	0.103	0.087	0.107
PER	0.085	0.085	0.087	0.087	0.089	0.095	0.089	0.102	0.084	0.093
Stock Index	0.102	0.097	0.102	0.093	0.099	0.099	0.095	0.100	0.091	0.106
Spread 10y3m	0.089	0.078	0.082	0.065	0.066	0.064	0.066	0.069	0.066	0.075
Spread 3m1y	0.096	0.064	0.100	0.084	0.094	0.084	0.090	0.094	0.086	0.097
Spread Corp.-1y	0.099	0.083	0.090	0.081	0.074	0.073	0.066	0.070	0.068	0.079
Spread Corp.-3m	0.094	0.081	0.089	0.076	0.078	0.068	0.071	0.065	0.065	0.064
US Spread Corp.-1y	0.110	0.103	0.109	0.097	0.101	0.089	0.091	0.082	0.090	0.072
Default Rate	0.100	0.083	0.102	0.079	0.110	0.097	0.105	0.092	0.108	0.098
CRB	0.109	0.101	0.110	0.096	0.110	0.087	0.108	0.082	0.103	0.086
Oil	0.109	0.084	0.102	0.080	0.097	0.091	0.096	0.079	0.104	0.104
Gold	0.106	0.095	0.103	0.088	0.104	0.072	0.103	0.075	0.105	0.087
M1	0.109	0.105	0.106	0.106	0.103	0.094	0.100	0.098	0.103	0.093
Average of proba.	0.091	0.073	0.088	0.070	0.083	0.067	0.080	0.066	0.082	0.070
Factor-augmented	0.065	0.031	0.062	0.028	0.062	0.038	0.054	0.036	0.061	0.045

Table 5: QPS for the various variables and for the two combining schemes

Horizon	Simple probit				TV-probit						
	α	β_1	β_2	β_3	State i	$\alpha(i)$	$\beta_1(i)$	$\beta_2(i)$	$\beta_3(i)$	p_{00}	p_{11}
$h=1$	1.925 (0.18)	0.455 (0.06)	-0.448 (0.08)	-0.473 (0.08)	0	3.944 (0.65)	2.599 (0.62)	-2.266 (0.62)	-0.708 (0.61)	0.544	0.999
					1	2.318 (0.94)	0.302 (0.13)	-0.446 (0.35)	-0.820 (0.25)		
$h=3$	1.971 (0.18)	0.516 (0.06)	-0.427 (0.08)	-0.355 (0.08)	0	8.076 (1.87)	3.754 (0.88)	-1.667 (0.41)	-0.275 (0.29)	0.999	0.164
					1	5.013 (0.94)	0.552 (0.13)	-1.607 (0.35)	0.815 (0.25)		
$h=6$	1.935 (0.18)	0.567 (0.06)	-0.278 (0.08)	-0.246 (0.08)	0	3.077 (0.48)	0.606 (0.12)	0.412 (0.17)	-0.759 (0.11)	0.999	0.999
					1	4.760 (2.45)	2.118 (1.16)	-1.131 (0.71)	-0.506 (0.44)		
$h=9$	2.088 (0.22)	0.849 (0.11)	-0.123 (0.08)	0.215 (0.12)	0	3.845 (0.80)	1.300 (0.32)	0.244 (0.26)	-0.381 (0.26)	0.332	0.999
					1	3.932 (0.58)	0.905 (0.27)	-0.738 (0.22)	1.287 (0.32)		
$h=12$	1.819 (0.16)	0.596 (0.07)	-0.112 (0.07)	-0.009 (0.08)	0	2.256 (0.26)	0.728 (0.11)	0.119 (0.09)	-0.067 (0.09)	0.999	0.219
					1	1.610 (0.56)	6.196 (3.74)	1.666 (0.81)	3.835 (2.61)		

Table 6: Estimated parameters of the factor-augmented probit models (standard errors in parenthesis)

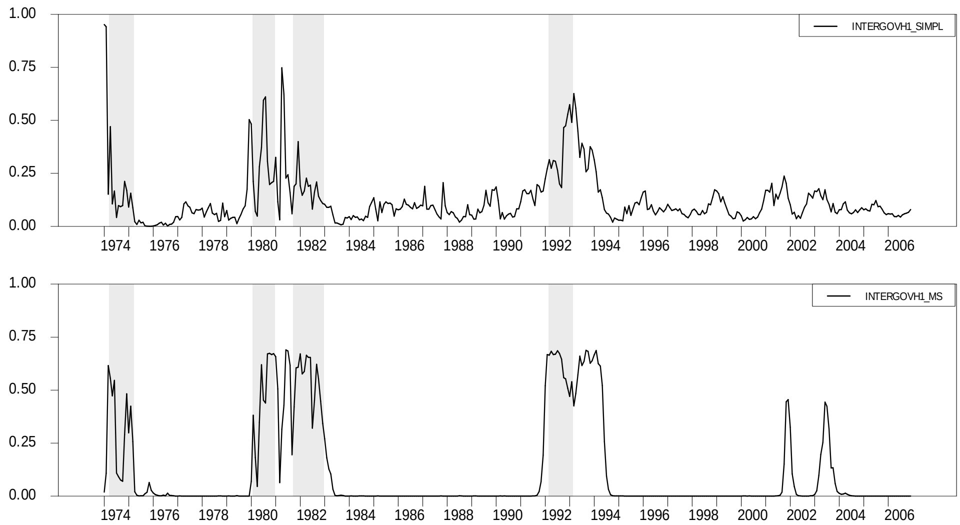

Figure 1: Predicted probability of being in recession one month ahead estimated from simple probit (top) and TV-probit (bottom) models using the spread between 3-month interbank rate and 1-year government bond. Shaded areas correspond to recession periods.

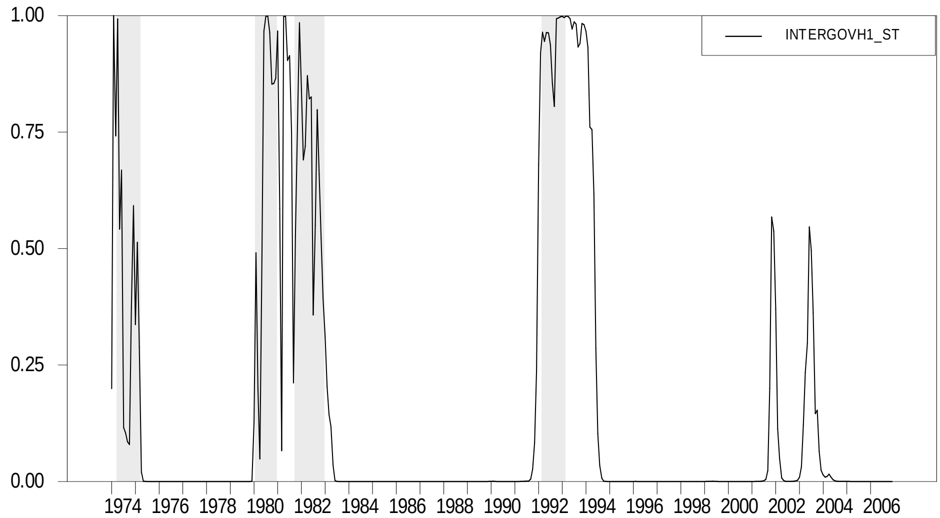

Figure 2: State probability of being in regime 1 estimated from a TV-probit model using the spread between 3-month interbank rate and 1-year government bond. Shaded areas correspond to recession periods.

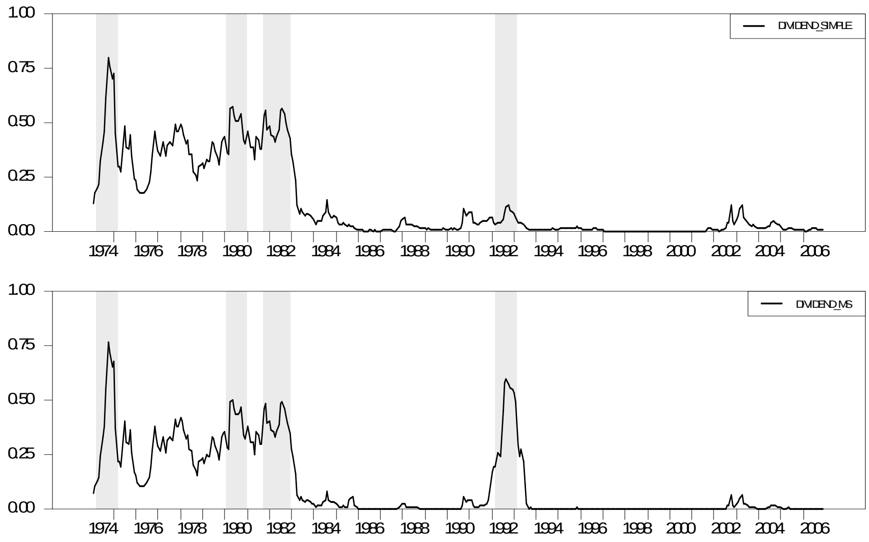

Figure 3: Predicted probability of being in recession one month ahead estimated from simple probit (top) and TV-probit (bottom) models using dividend yield of stock market. Shaded areas correspond to recession periods.

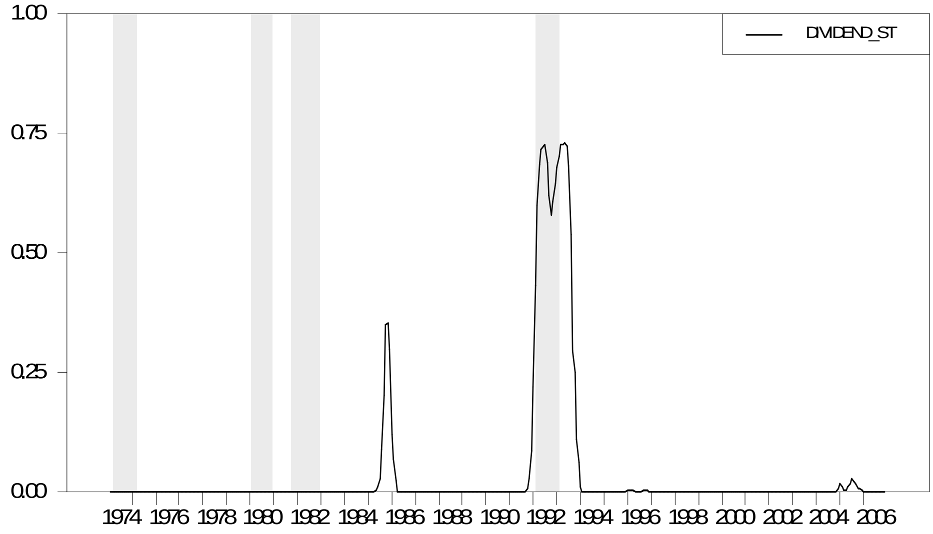

Figure 4: State probability of being in regime 1 estimated from a TV-probit model using dividend yield of stock market. Shaded areas correspond to recession periods.

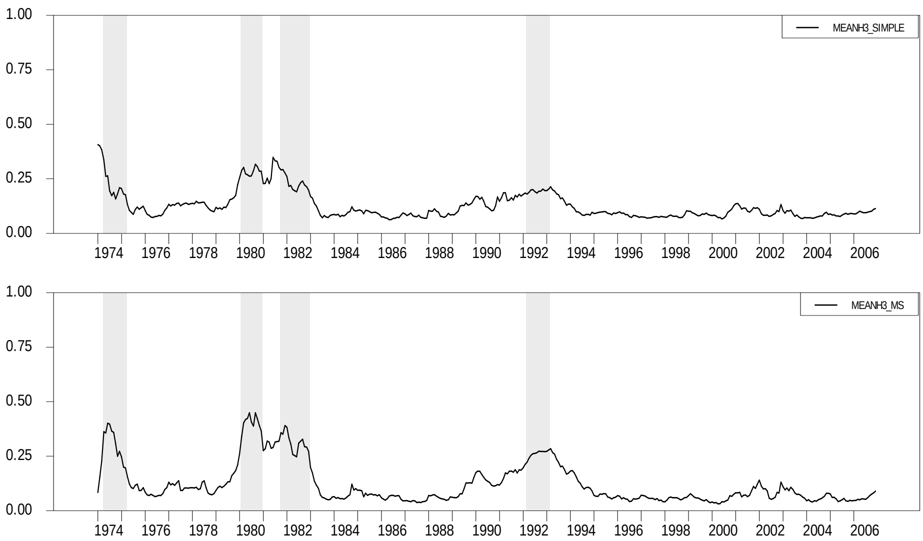

Figure 5: Average of all in-sample predicted probabilities with $h = 3$ estimated from simple probit (top) and TV-probit (bottom) models. Shaded areas correspond to recession periods.

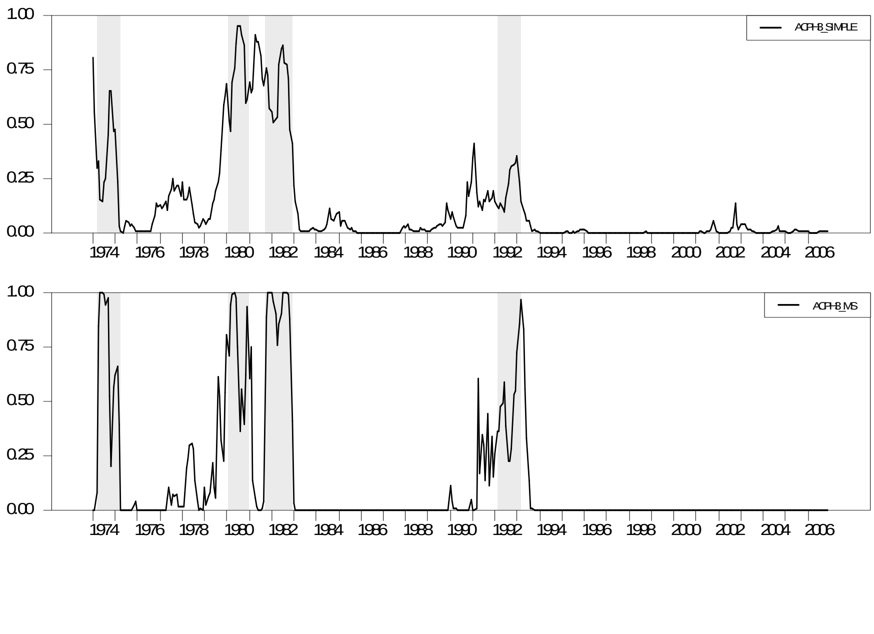

Figure 6: In-sample predicted probabilities with $h = 3$ estimated from factor-augmented simple probit (top) and factor-augmented TV-probit (bottom) models. Shaded areas correspond to recession periods.

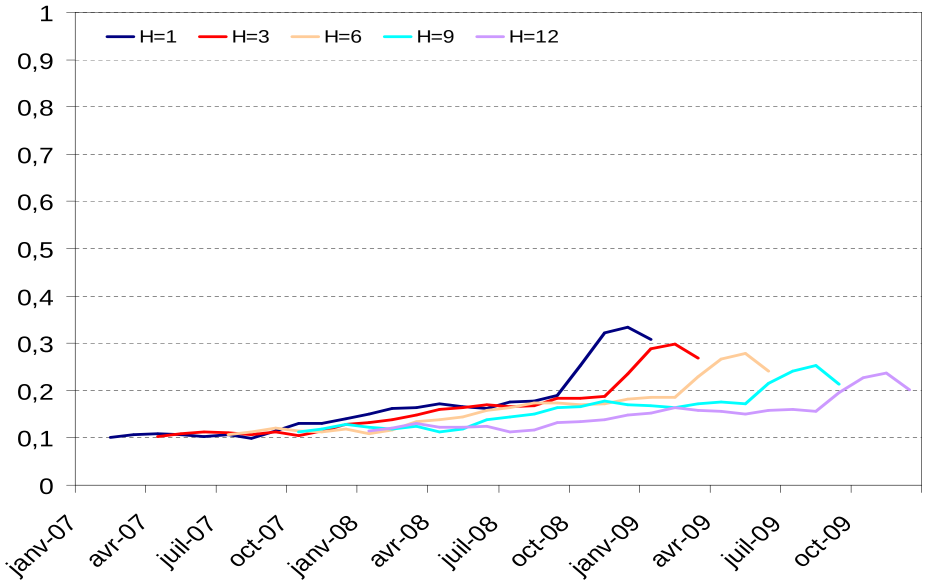

Figure 7: Average of out-of-sample predicted probabilities from simple probit models, for $h = 1, 3, 6, 9, 12$ months.

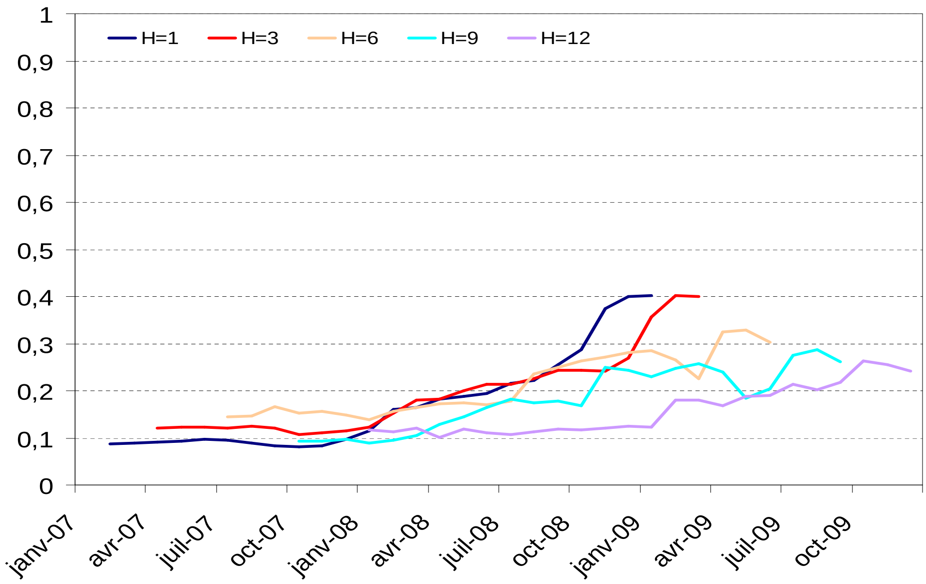

Figure 8: Average of out-of-sample predicted probabilities from TV-probit models, for $h = 1, 3, 6, 9, 12$ months.

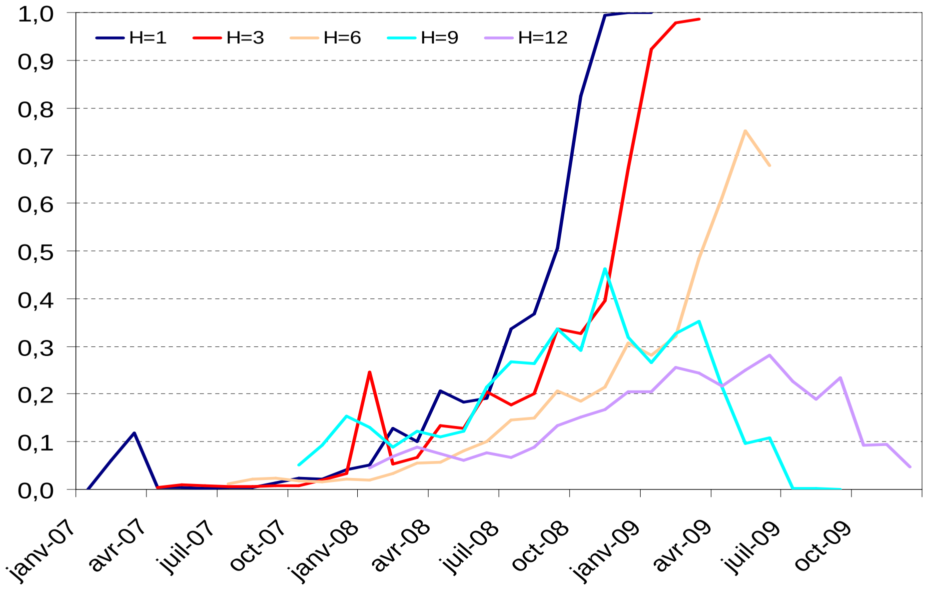

Figure 9: Out-of-sample forecasts from factor-augmented and simple probit models, for $h = 1, 3, 6, 9, 12$ months.

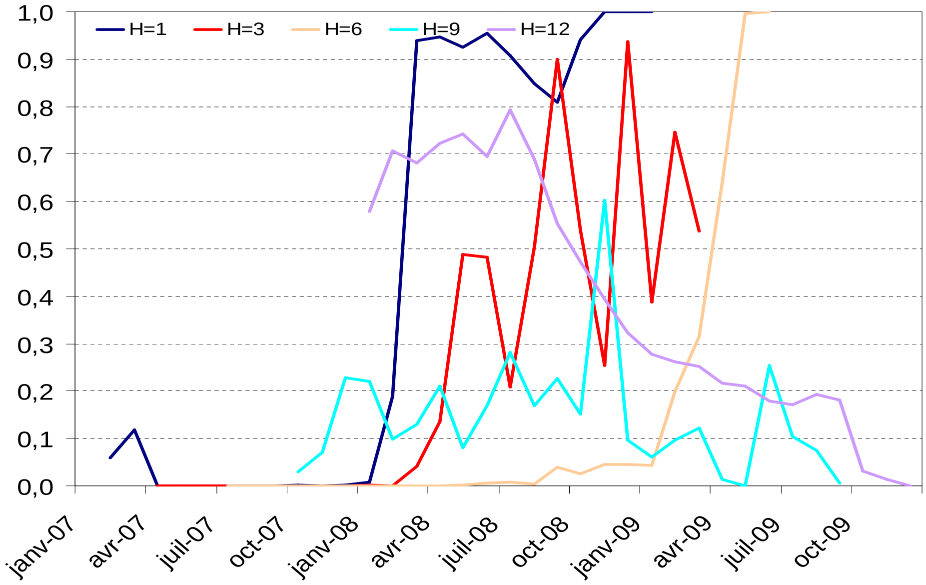

Figure 10: Out-of-sample forecasts from factor-augmented TV-probit models, for $h = 1, 3, 6, 9, 12$ months.

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