Forecasting euro area recessions by combining financial information

Christophe Bellégo
INSEE-CREST, Malakoff, 92240, France
Email: christophe.bellego@ensae.fr

Laurent Ferrara*
Banque de France, International Macroeconomics Division, Paris, 75001, France
Email: laurent.ferrara@banque-france.fr
*Corresponding author

Abstract: The last two macroeconomic recessions in the euro area in 2008–2009 and 2011–2013 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 binary response models associated with information combination. For various forecast horizons, we provide a readable and leading signal of recession by combining information according to two combining schemes. First we average recession probabilities and second we linearly combine variables through a factor model in order to estimate an innovative Factor-Augmented probit model. Out-of-sample results over the periods 2007–2009 and 2011–2013 show that financial variables would have been helpful in giving accurate and timely recession signals in real-time.

Keywords: macroeconomic forecasting; recession; financial markets; combining forecasts.

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Biographical notes: Christophe Bellégo is an Economist at Insee, the French National Statistical Office. Previously, he was an Economist in Charge of Public Policy Evaluations at the French Ministry for Industry. He currently comes to the end of a PhD thesis, at CREST, on empirical industrial organisation. He is a Former student of Ecole Normale Supérieure (Cachan) and a graduate from ENSAE.

Laurent Ferrara is Head of the International Macroeconomics Division at the Banque de France in Paris, in Charge of the Outlook and Macroeconomic Forecasting for Advanced Economies as well as Global Policy Issues. He is also Adjunct Professor of Economics at the University of Paris West. He holds a PhD in Statistics from the University of Paris North and a Research Habilitation in Economics from the University of Paris 1–Panthéon–Sorbonne. His academic
1 Introduction

The year 2008 has painfully recalled to the economic community that business cycles were still alive. In spite of the ‘Great Moderation’ theory arguing in favour of the reduction in the amplitude of cycles (see among others McConnel and Perez-Quiros, 2000; Giannone et al., 2008), a severe recession has affected simultaneously most of the industrialised countries in the following of the US sub-prime credit crisis. More recently, a recession affected more specifically the euro area, from 2011 to 2013, mainly related to the sovereign bonds crisis in some countries and its feedback loop with a banking crisis. 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. We evaluate the ability of a dataset of financial variables to predict business cycle turning points in the aggregate euro area, for various forecast horizons ranging from 1 to 12 months. It is well known from the literature that financial variables possess a macroeconomic predictive power (see, among others, Stock and Watson, 2003). In this paper, historical euro area financial variables from early 1970s are used for the first time in this framework, such as, for example, various term spreads, stock markets variables and commodities prices.

Binary response models, such as probit models, have widely proved their ability to forecast business cycles, we refer for example to Chauvet and Potter (2002, 2005), Kauppi and Saikkonen (2008) or Rudebusch and Williams (2009) for recent empirical applications. In this paper, we extend probit models by combining information according to two combining schemes, allowing estimated probabilities of recessions few months ahead. First we average predicted recession probabilities stemming from standard probit models applied to each variable and second we linearly combine variables through a static factor model in order to estimate a Factor-Augmented probit model. This latter Factor-Augmented probit approach has been put forward in Bellégo and Ferrara (2012).

As a result, we provide a readable and leading signal of recession by combining information, since 1973. In-sample results show that this approach enables to correctly replicate past recessions from 1973 to 2006 and from 1973 to 2010. Out-of-sample results over the periods 2007–2009 and 2011–2013 suggest that financial variables would have been helpful in anticipating a recession signal in the euro area few months ahead.

In the next section, we describe the econometric framework that we implement, including the standard binary response model and the details of the two combining schemes. In Section 3, we describe the dataset that we use. The in-sample analysis that we carry out is presented in Section 4. Section 5 presents the results of the out-of-sample analysis and the last section concludes.
2 Econometric modelling

In this section, we describe the econometric approaches that we implement. We first present the binary response model that we use to get forecasted probabilities of recession for a given horizon $h$, based on a single financial variable. Then we describe the two aggregation schemes that we implement assuming that we have at disposal a dataset of $n$ financial variables. In this respect we put forward an innovative Factor-Augmented probit model (see Bellégo and Ferrara, 2012) that first linearly combines variables and then put the estimated common factor into a binary response probit model. As a benchmark, we compare this approach with a classical scheme that averages estimated probabilities of recession.

2.1 Binary response modelling

We assume that we observe the values of a binary variable $(r_t)$ 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 $(r_t)$, stem from a latent continuous variable, denoted $(y_t)$, defined by the following linear equation, for all $t$;

$$y_t = \alpha + \beta x_{t-k} + \epsilon_t,$$

where $x_{t-k}$ is an univariate explanatory variable, $k \geq 0$ is a lag, $\beta$ is the parameter and $(\epsilon_t)$ is the error term supposed to follow a strong white noise process with finite variance $\sigma^2_\epsilon$. The distribution of $(\epsilon_t)$ is discussed below. Most of the time, in empirical applications, the explanatory variable is delayed with a given lag $k \geq 1$ that corresponds to the forecast horizon.

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

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

For each date $t$, it can be easily proved that the conditional probability that an economic recession occurs, conditionally on $\Omega_t$, the whole information set available at date $t$, is given by the standard model :

$$P(r_t = 1|\Omega_t) = P(r_t = 1|x_{t-k}) = C(-\alpha - \beta x_{t-k}),$$

where $C(.)$ is the cumulative density function of the variable $(\epsilon_t)$. The probit model is defined by assuming that the error term $(\epsilon_t)$ is Gaussian, that is $C(.)$ is the cumulative density function (cdf) of the standard Gaussian distribution. The model given by equations (1)–(3) is referred to as the standard probit model in the remaining of the paper.

2.2 Combining probabilities through averaging

Assume now that we observe a set of $n$ explanatory variables $(x^j_t)$, for $j = 1, \ldots, n$. It is well known that combining probabilities of recession stemming from various models or variables can improve the accuracy of the results obtained from a single predictor. For example, in the framework of the building of probabilistic indicators of business cycles,
Anas et al. (2008) have developed recession indicators for real-time detection based on a weighted average of recession probabilities.

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

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

(4)

where $\hat{P}^j(r_{t+h} = 1|\Omega_t)$ stems from equations (1)–(3) estimated for each individual financial variables $(x_j^t)$, for $j = 1, \ldots, n$.

Note that we have tried various weighting schemes in the empirical part of the paper, but uniform weighting provides the best outcomes as regards our measure of accuracy (see Section 2.3). However, more sophisticated statistical averaging methods could be used to improve the results, as for example Bayesian averaging (see King et al., 2007; Billio et al., 2012).

2.3 Combining variables through a factor model

An often used alternative to combine information is to linearly combine variables into a small number of factors before putting them into a standard econometric model. 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 summarise macroeconomic information. Such approaches have been extensively used in several directions, especially for macroeconomic forecasting; we refer for example to Stock and Watson (2006), Marcellino and Schumacher (2010) or Barhoumi et al. (2010) for applications, as well as to Barhoumi et al. (2013) for a review. Here, we focus on the Factor-Augmented probit modelling as put forward by Bellégo and Ferrara (2012).

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

$$x_t = \chi_t + \xi_t,$$

(5)

where $x_t = (x_1^t, \ldots, x_n^t)'$ is a vector of $n$ stationary time series and it is assumed that the series have zero mean and semi-definite positive covariance 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 $F_t = (F_1^t, \ldots, F_r^t)'. \Lambda$ is the loading matrix and $\xi_t = (\xi_1^t, \ldots, \xi_n^t)'$ 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 $r = 3$. After having estimated the factors $\hat{F}_t$, we use them as explanatory variables into the model defined by equation (3) in order to get a probability of being in recession $h$-step ahead. This approach is referred to as Factor-Augmented probit modelling.
3 Data selection

In this section, we discuss the choice of the reference dating chronology of turning points as well as the choice of the variables that we integrate into our analysis.

A constraint for practitioners using probit models in business cycle analysis is that the variable \( r_t \), namely the recession/expansion phases of the cycle, has to be known \textit{a priori}, before the estimation step. When dealing with the US business cycle, the reference chronology is given by the NBER Dating Committee. As regards euro area aggregated economic cycles, the CEPR updates a turning point chronology and Eurostat provides a dating chronology for both business and growth cycles (see Mazzi and Savio, 2007; Anas et al., 2007). In this paper, we use the business cycle turning point chronology of Eurostat proposed by Anas et al. (2007). They provide both a quarterly chronology based on GDP and a monthly chronology based on the industrial production index (IPI). As we need a monthly reference for our exercise, we choose the IPI chronology except for the year 2001 in which for the first time in euro area countries an industrial recession occurred without a global recession. In fact, by comparison with the CEPR dating, this chronology assumes the existence of a double dip in early eighties, in line with the NBER dating for the US. As a consequence, we retain four recession periods between 1974 and 2006, from peak to trough: March 1974–March 1975, January 1980–December 1980, September 1981–December 1982 and February 1992–February 1993. As regards the two recent recessions in 2008–2009 and 2011–2013, we apply the same methodology and we retain February 2008 as peak and September 2009 as trough, while we get August 2011 as peak and February 2013 as trough.

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 1970s to 2006, the euro area has only experienced four recessions. Thus, we need long historical series. Unfortunately, the volume of recent financial data is incredibly large, but getting historical financial data is not an 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 12 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 (see Duarte et al., 2005). 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 minus 3-months term spread, has been assessed in many 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 (P/E) ratio. 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 P/E ratio 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 P/E ratio 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 macro-economy 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, the monetary aggregate (M1 seasonally adjusted) is also used in this paper. Note also that other variables, such as the Euro Trade Weighted Index or the US default rate, 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 1.

Table 1 Data description

<table>
<thead>
<tr>
<th>Variable</th>
<th>Starting date</th>
<th>Transformation</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>EA dividend yield</td>
<td>January 1973</td>
<td>In level</td>
<td>Datastream</td>
</tr>
<tr>
<td>EA P/E ratio</td>
<td>January 1973</td>
<td>In level</td>
<td>Datastream</td>
</tr>
<tr>
<td>EA stock index</td>
<td>January 1973</td>
<td>Growth rate over 6 months</td>
<td>Datastream</td>
</tr>
<tr>
<td>German spread: 10 years gov. bond rate – 3 months interbank rate</td>
<td>September 1972</td>
<td>In level</td>
<td>Deutsche Bundesbank</td>
</tr>
<tr>
<td>German spread: 3 months interbank rate – 1 year gov bond rate</td>
<td>September 1972</td>
<td>In level</td>
<td>Deutsche Bundesbank</td>
</tr>
<tr>
<td>German spread: corporate rate – 1 year gov bond rate</td>
<td>September 1972</td>
<td>In level</td>
<td>Deutsche Bundesbank</td>
</tr>
<tr>
<td>German spread: corporate rate – 3 months interbank rate</td>
<td>January 1970</td>
<td>In level</td>
<td>Deutsche Bundesbank</td>
</tr>
<tr>
<td>US spread: corporate BAA rate – 1 year gov bond rate</td>
<td>January 1970</td>
<td>In level</td>
<td>US treasury and Moody’s</td>
</tr>
<tr>
<td>CRB spot index</td>
<td>January 1970</td>
<td>Growth rate over 6 months</td>
<td>Commodity Research Bureau</td>
</tr>
<tr>
<td>Oil spot price</td>
<td>January 1970</td>
<td>Growth rate over 6 months</td>
<td>Bloomberg</td>
</tr>
<tr>
<td>Gold price</td>
<td>January 1970</td>
<td>Growth rate over 6 months</td>
<td>Gold Bullion LBM</td>
</tr>
<tr>
<td>EA M1 sa</td>
<td>January 1970</td>
<td>Growth rate over 6 months</td>
<td>OECD</td>
</tr>
</tbody>
</table>
4 In-sample analysis

4.1 Variable-specific analysis

For each considered variable \((x_j^t)\), \(j = 1, \ldots, n = 12\), we first determine whether it 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 \(h\) corresponds to lag \(k\) in equation (3). For the two sample periods under investigation, namely 1974–2006 and 1974–2010, we estimate parameters by maximum likelihood. We use these two samples to implement two out-of-sample forecasts over the periods 2007–2009 and 2011–2013 later in this paper. Thus, for each variable \((x_j^t)\), we obtain the estimated probability of being in recession \(h\)-steps ahead, denoted \(\hat{P}_j(r_{t+h} = 1|\Omega_t)\).

To assess the ability of each variable \((x_j^t)\) 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:

\[
QPS(j, h) = \frac{1}{T} \sum_{t=1}^{T-h} (r_{t+h} - \hat{P}_j(r_{t+h} = 1|\Omega_t))^2.
\]

The QPS can be understood as a measure analogue of mean squared error and ranges from zero (perfect match between realisation and forecast) to one (perfect discordance between realisation and forecast). Forecasting and comparing probabilities of macroeconomic events is not an easy task for practitioners but QPS is generally considered as a standard measure in the business cycle literature (see Seillier-Moiseiwitsch and Dawid, 1993; Lahiri and Yang, 2013a). In this paper, we focus only on the absolute comparison between QPS, knowing that some tests for discriminating among binary response models have been recently put forward in the literature (see Lahiri and Wang, 2013b).

Based on QPS results presented in Table 2, it turns out that the most relevant variable is the 10-years minus 3-months term spread, especially for \(h = 3\). 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 \(h = 3\), while the stock index series seems to contain less useful information. Variables corresponding to commodity prices and the monetary aggregate provide more uncertain recession signals. It is consistent with the fact that recent recessions are less connected to commodities boom, compared to the macroeconomic implications of 1973 and 1979 oil crises. Finally, QPS depicts that the recession of 2008–2009 was hard to accurately model. QPS are consistently higher for the period 1974–2010 period than for the period 1974–2006.

4.2 Combining probabilities through averaging

Based on the previous forecasted probabilities, we first look at the probability given by equation (4). For example, results for \(h = 6\) are presented in Figure 1. From this graph, we observe that this probability tends to increase for each recession but does never reach the natural threshold value of 0.50. From Table 2, we observe that combining probabilities enables to improve the outcomes in QPS terms by comparison with univariate estimated
standard probit models. However, QPS results do not appear to be as good as those obtained with the Factor-Augmented model. Moreover, the 10-years minus 3-months term spread consistently overtakes the averaging combination. Like the univariate approaches, the recession of 2008–2009 downgrades the detection performance of the averaging model. It is noteworthy that, as with the previous scheme, the lowest QPS is reached for an horizon of 9 months, that can be seen as the average lead over the business cycle.

Table 2  QPS criteria for the 12 variables, for the two combining schemes (FA probit and Averaging) and for various forecasting horizons. For each case, two sample sizes are considered: 1974–2006 (first column) and 1974–2010 (second column)

<table>
<thead>
<tr>
<th>Variables</th>
<th>74-06</th>
<th>74-10</th>
<th>74-06</th>
<th>74-10</th>
<th>74-06</th>
<th>74-10</th>
<th>74-06</th>
<th>74-10</th>
<th>74-06</th>
<th>74-10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dividend yield</td>
<td>0.074</td>
<td>0.083</td>
<td>0.076</td>
<td>0.089</td>
<td>0.089</td>
<td>0.105</td>
<td>0.096</td>
<td>0.119</td>
<td>0.098</td>
<td>0.124</td>
</tr>
<tr>
<td>PER</td>
<td>0.081</td>
<td>0.092</td>
<td>0.082</td>
<td>0.091</td>
<td>0.088</td>
<td>0.099</td>
<td>0.094</td>
<td>0.110</td>
<td>0.095</td>
<td>0.115</td>
</tr>
<tr>
<td>Stock index</td>
<td>0.101</td>
<td>0.114</td>
<td>0.100</td>
<td>0.111</td>
<td>0.101</td>
<td>0.115</td>
<td>0.102</td>
<td>0.121</td>
<td>0.103</td>
<td>0.125</td>
</tr>
<tr>
<td>Spread 10y3m</td>
<td>0.083</td>
<td>0.104</td>
<td>0.075</td>
<td>0.093</td>
<td>0.065</td>
<td>0.080</td>
<td>0.066</td>
<td>0.081</td>
<td>0.066</td>
<td>0.084</td>
</tr>
<tr>
<td>Spread 3m1y</td>
<td>0.092</td>
<td>0.106</td>
<td>0.091</td>
<td>0.102</td>
<td>0.087</td>
<td>0.095</td>
<td>0.084</td>
<td>0.096</td>
<td>0.080</td>
<td>0.101</td>
</tr>
<tr>
<td>Spread corp1y</td>
<td>0.090</td>
<td>0.127</td>
<td>0.082</td>
<td>0.125</td>
<td>0.070</td>
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<td>0.065</td>
<td>0.109</td>
<td>0.074</td>
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</tr>
<tr>
<td>Spread corp3m</td>
<td>0.086</td>
<td>0.119</td>
<td>0.080</td>
<td>0.113</td>
<td>0.070</td>
<td>0.101</td>
<td>0.066</td>
<td>0.095</td>
<td>0.065</td>
<td>0.092</td>
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<tr>
<td>US spread</td>
<td>0.105</td>
<td>0.120</td>
<td>0.104</td>
<td>0.126</td>
<td>0.096</td>
<td>0.127</td>
<td>0.087</td>
<td>0.122</td>
<td>0.084</td>
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<tr>
<td>CRB</td>
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<td>0.122</td>
<td>0.105</td>
<td>0.124</td>
<td>0.105</td>
<td>0.126</td>
<td>0.105</td>
<td>0.127</td>
<td>0.100</td>
<td>0.119</td>
</tr>
<tr>
<td>Oil</td>
<td>0.105</td>
<td>0.128</td>
<td>0.104</td>
<td>0.128</td>
<td>0.098</td>
<td>0.123</td>
<td>0.095</td>
<td>0.118</td>
<td>0.102</td>
<td>0.123</td>
</tr>
<tr>
<td>Gold</td>
<td>0.102</td>
<td>0.125</td>
<td>0.100</td>
<td>0.123</td>
<td>0.097</td>
<td>0.120</td>
<td>0.098</td>
<td>0.121</td>
<td>0.104</td>
<td>0.126</td>
</tr>
<tr>
<td>M1</td>
<td>0.104</td>
<td>0.124</td>
<td>0.101</td>
<td>0.119</td>
<td>0.099</td>
<td>0.111</td>
<td>0.097</td>
<td>0.105</td>
<td>0.098</td>
<td>0.109</td>
</tr>
<tr>
<td>FA probit</td>
<td>0.061</td>
<td>0.059</td>
<td>0.060</td>
<td>0.054</td>
<td>0.050</td>
<td>0.058</td>
<td>0.048</td>
<td>0.068</td>
<td>0.057</td>
<td>0.075</td>
</tr>
<tr>
<td>Averaging</td>
<td>0.086</td>
<td>0.104</td>
<td>0.083</td>
<td>0.101</td>
<td>0.078</td>
<td>0.098</td>
<td>0.076</td>
<td>0.098</td>
<td>0.079</td>
<td>0.100</td>
</tr>
</tbody>
</table>

4.3 Combining variables through a factor model

We implement now the Factor-Augmented probit approach. The first three estimated factors account for around 60% of the total variance of financial variables, which is reasonable in such empirical studies. It is noteworthy that the first factor is mostly 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 $\hat{F}_t$, we use them as explanatory variables into the model defined by equation (3) in order to get a probability of being in recession $h$-step ahead. An interesting result is 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. Estimated probability is presented in Figure 2, for $h = 6$. Eyeballing the figure suggests that the Factor-Augmented model does a reasonably
good job in replicating business cycle phases. Indeed, estimated recession probabilities provide a good match with reference dates of recession. When comparing with results obtained for each individual variable from the QPS point of view (Table 2), we note a clear improvement using this approach for all horizons. The Factor-Augmented probit model always outperforms the averaging combination and the univariate estimated standard probit models. Moreover, the QPS computed over the period 1974–2010 (contained in the column 74–10 of Table 2) show that the recession of 2008–2009 is really well detected for $h = 1$, $h = 3$ and $h = 6$ by comparison with other approaches. Thus, it seems that this model clearly allows an improvement in identifying and anticipating recession phases. The Factor-Augmented probit approach reaches its minimal QPS for $h = 9$. This average lead of 9 months is consistent with the outcomes of the empirical literature trying to relate financial variables with macroeconomic business cycles.

**Figure 1** Average of all in-sample predicted probabilities with $h = 6$ estimated from standard probit. Blue line corresponds to recession periods (see online version for colours)

### 4.4 Decision rule

It is always useful for policy-makers to get a decision rule instead of having a single probability to interpret. Therefore, we propose to set up a decision rule 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 maximises the corrected contingency coefficient put forward by Artis et al. (2004) and based on the Pearson’s goodness-of-fit criterion. This corrected contingency coefficient can be seen as a measure of dependence between to binary variables (see Appendix for details).

Estimated thresholds are given in Table 3 for each forecast horizon $h$ and for each combining scheme. For example, when using the average of all probabilities estimated through standard probit models (equation (4)), the critical threshold stands between 0.16
and 0.19 for all horizons over the sample 1974–2006. Over the sample 1974–2010, the estimated critical values are very similar, indicating a stability of the results. Estimating the Factor-Augmented probit model generally leads to higher critical thresholds than those obtained with the previous combining scheme, confirming that this approach provides a better fit. But it is noteworthy that the contingency coefficients have not been systematically improved, pointing out that, when using this specific ad hoc rule, it is not necessary to get high values of the estimated probabilities of recession before sending a signal. We also note that the corrected contingency coefficients for \( h = 12 \) are lower than those obtained for other horizons, pointing out a lower goodness-of-fit at this specific horizon.

**Figure 2** In-sample predicted probabilities with \( h = 6 \) estimated from the factor-augmented probit model. Blue line corresponds to recession periods (see online version for colours)

<table>
<thead>
<tr>
<th>Table 3</th>
<th>Estimated critical thresholds for the decision rule and corresponding corrected contingency coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td><strong>Averaging probabilities</strong></td>
</tr>
<tr>
<td>Horizon</td>
<td>Threshold</td>
</tr>
<tr>
<td>( h = 1 )</td>
<td>0.19</td>
</tr>
<tr>
<td>( h = 3 )</td>
<td>0.16</td>
</tr>
<tr>
<td>( h = 6 )</td>
<td>0.18</td>
</tr>
<tr>
<td>( h = 9 )</td>
<td>0.19</td>
</tr>
<tr>
<td>( h = 12 )</td>
<td>0.16</td>
</tr>
</tbody>
</table>

Such critical thresholds are going to be useful for out-of-sample forecasting, as we will be able to send a signal well before reaching the natural 0.5 threshold often used in this kind of literature on business cycle analysis.
5 Out-of-sample analysis

The objective of this section is to evaluate the ability of the two previous approaches to anticipate out-of-sample the occurrence of the last two recessions in the euro area in 2008–2009 and 2011–2013. As financial data are generally not revised, this experiment could be classified as a quasi-real-time experiment.

Let’s first focus on the great recession of 2008–2009. In this respect, we first 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, $\hat{P}(r_{t+h} = 1|\Omega_t)$, according to the two combining schemes previously presented. As, obviously, $(r_t)$ is unknown over the forecasting period, it is not possible to re-estimate the models as new data become available. The solution that we implement 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 as soon as new data are released. Last, for each forecast horizon $h$, we apply the decision rule involving the critical thresholds estimated previously in Table 3 in order to send a signal of recession or expansion $h$ months ahead.

Out-of-sample forecasting results obtained when averaging all probabilities, are presented in Figure 3. As expected from the in-sample analysis, the natural threshold of 0.50 has not been crossed, pointing out the usefulness of estimated critical thresholds estimated before. When using those critical thresholds, the estimated dates for peaks are given in Table 4. The salient fact is that, by using this decision rule, a peak is identified in February 2008 with a forecasting horizon $h = 3$, that is at the time of the reference peak, which is a quite good result in real-time.

### Table 4  Out-of-sample estimation of peaks in the 2008–2009 and 2011–2013 recessions using the decision rule involving critical thresholds

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$h = 1$</td>
<td>$h = 3$</td>
<td>$h = 6$</td>
<td>$h = 9$</td>
<td>$h = 12$</td>
<td></td>
</tr>
</tbody>
</table>

| 2011–2013 recession: Reference peak in August 2011 |
|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| $h = 1$ | $h = 3$ | $h = 6$ | $h = 9$ | $h = 12$ |
| Factor-augmented probit | July 2011 | September 2011 | January 2012 | May 2012 | No signal |

Out-of-sample forecasting results obtained with the second combining scheme, that is when estimating Factor-Augmented models, are presented in Figure 4. For $h = 1$ we get a high probability of recession reaching a maximum of 0.93 in December 2008. The critical threshold of 0.25 was crossed in April 2008, indicating thus a peak in March 2008. For all other horizons, estimated probabilities are lower and stay below 0.50. However, when
using the decision rule with the estimated critical thresholds, we get that a persistent signal of recession could have been sent in 2008 (see the estimated dates for peaks in Table 4).

Thus, from this quasi-real-time experiment, we retain that as the end of March 2008, we would have been able to send a first signal of recession in the euro area.

Let’s now focus on the second recession in 2011–2013. In this respect, we take first the previous models estimated over the period 1974–2010 and we use them with data from January 2011 to December 2013. Thus, for each month $t$, from January 2011 to December 2013, we estimate the probability of being in recession $h$ months ahead, $P(r_{t+h} = 1|\Omega_t)$, according to the two combining schemes. Out-of-sample forecasting results obtained when averaging all probabilities are presented in Figure 5. Again, we note that recession probabilities are low and stay below 0.40 over the sample. However, when using the critical thresholds, we get an estimated peak in August 2011, that is just one month after the reference peak. For all forecasting horizons, a signal is given by this approach, the lag obviously increasing with the horizon.

Results stemming from the Factor-Augmented probit model are presented in Figure 6. Those results are striking in the sense that the models provide very high probabilities, from $h = 1$ to $h = 9$. Especially those values go close to the maximum for $h = 1, 3$. For $h = 1$ we identify a peak at the correct reference date in July 2011. This signal could have been sent in real-time as soon as the data of August 2011 were available.

It should be stressed that the recession signals obtained with our approaches provide accurate estimates of turning points but would have been really leading in real-time if compared with official announcements. Indeed, recall that the CEPR announcement of the February 2008 peak was released at the end of March 2009 while the announcement of the 2011 August peak was done mid-November 2012. Thus, considering that, using our best results, the 2008 peak was detected with the data related to March 2008 (available the last
day of March 2008) and the 2011 peak with the data related to August 2011 (available the last day of August 2011), this means that we are able to get an average lead of 12 months and 15 months, respectively, vis-à-vis official announcements of euro area recessions. In this respect, the tools that we put forward enable to send early signals of recession in real-time.

**Figure 4** Out-of-sample forecast of the 2008–2009 recession from factor-augmented probit models, for $h = 1, 3, 6, 9, 12$ months (see online version for colours)

**Figure 5** Average of out-of-sample predicted probabilities of the 2011–2013 recession from standard probit models, for $h = 1, 3, 6, 9, 12$ months (see online version for colours)
6 Conclusions

Forecasting recessions is a great challenge for macroeconomic forecasters. In a well known paper, Hamilton (2011) concludes that the best that econometricians can do is probably to nowcast recessions, that is to recognise a turning point as soon as it occurs, or soon after. This statement is confirmed by our analysis in which we propose to evaluate the ability of a set of financial variables to predict business cycle turning points in the euro area by using binary response models associated with two information combining schemes. First we combine recession probabilities and second we estimate innovative Factor-Augmented probit models. Both combining approaches enable to improve in-sample goodness-of-fit since early 1970s, by comparison with each individual variable. When using both approaches in quasi-real-time since 2007, we would have been able to send early signals of recession, as end of March 2008 (for the 2008–2009 recession) and as end of August 2011 (for the 2011–2013 recession), that is as soon as the recession occurred, but well before their official announcements by the CEPR. The approach we put forward can be useful for practitioners aiming at monitoring in real-time recession risks.

Acknowledgements

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References


Forecasting euro area recessions by combining financial information


Notes

1 The inclusion of a greater number of factor into the probit models has not been found statistically significant.

2 Parameter estimates, for all forecast horizons, are available upon request.

Appendix

Contingency coefficient

The Pearson’s goodness-of-fit test tests the null hypothesis of independence of two binaries time series. Hence this method need to transform 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:

\[
\hat{\chi}^2 = \sum_{i=0}^{1} \sum_{j=0}^{1} \left( \frac{n_{ij} - (n_{i} \cdot n_{j}/N))^2}{(n_{i} \cdot n_{j}/N)} \right),
\]

(A1)

where the \( n_{ij} \) are described in Table A1. 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.
The $\chi^2$ statistics given in equation (A1) 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 $2 \times 2$ 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 et al. (2004), given by:

$$CC_{corr} = \frac{CC}{\sqrt{0.5}} \times 100,$$  \hspace{1cm} (A2)

where

$$CC = \sqrt{\frac{\chi^2}{N + \chi^2}}.$$  \hspace{1cm} (A3)

### Table A1  Contingency table

<table>
<thead>
<tr>
<th>Datation $i$</th>
<th>Probability $j$</th>
<th>Expansion</th>
<th>Recession</th>
<th>Subtotal</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Expansion</td>
<td>$n_{00}$</td>
<td>$n_{01}$</td>
<td>$n_0$</td>
</tr>
<tr>
<td></td>
<td>Recession</td>
<td>$n_{10}$</td>
<td>$n_{11}$</td>
<td>$n_1$</td>
</tr>
<tr>
<td>Subtotal</td>
<td></td>
<td>$n_{0}$</td>
<td>$n_{1}$</td>
<td>$N$</td>
</tr>
</tbody>
</table>

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