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Macro-financial linkages and business cycles: A factor-augmented probit approach ☆

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ABSTRACT

In this paper, we analyze macro-financial linkages in the euro area by implementing an innovative factor-augmented probit model estimated using a large database. In particular, our model specification enables the identification of the leading influence of financial variables on euro area business cycles, in addition to the coincident information conveyed by standard macroeconomic variables. We also point out that dynamic factor models lead to more accurate replication of business cycles than static ones.

1. Introduction

Financial variables have been widely recognized in the literature as playing a major role in macroeconomic fluctuations (see among others Stock and Watson, 2003). Especially in business cycle analysis, parametric modeling is often used by economists in central banks or governmental institutions in order to assess periodically the probability of being in a given phase of the business cycle, defined here in the NBER sense by the alternation of expansion and recession phases. In this respect, binary response models, such as logit and probit models, have proved to be of great interest for practitioners aiming at monitoring the business cycle based on financial information. The empirical literature on this topic is huge but among the recent papers we refer for example to Chauvet and Potter (2002), Estrella et al. (2003), Pelaez (2007), Kauppi and Saikkonen (2008) or Rudebusch and Williams (2009) for the US and to Moneta (2005) for the euro area as a whole.

Recently, another strand of the literature in applied macroeconomics has focused on econometric modeling in a data-rich environment. In this respect, dynamic factor models have proved their usefulness, especially in order to nowcast or forecast macroeconomic variables. Among the recent empirical literature on this topic, we refer for example to the papers of Boivin and Ng (2006), Schumacher (2010), Giannone et al. (2008) or Barhoumi et al. (2010). Generally, the factor estimation step is carried out either by using standard statistical methods of dimension reduction within a static framework (Stock and Watson, 2002) or by using estimation methods that allow a richer dynamic behavior for the factor (Forni et al., 2005, or Doz et al., 2011).

In this paper, we reconcile both strands of the literature by putting forward a factor-augmented probit model that allows to get for each date a probability of recession conditionally to a large informational set. This conditional probability is estimated from a probit model that includes as explanatory variables the estimated dynamic or static factors. We implement this approach in order to analyze business cycles in the euro area from 1974 to 2008 by using a set of macroeconomic and financial variables. Especially, we point out the leading role of financial variables for turning point detection.

Similar approaches have been implemented in the forecasting framework by Bellégo and Ferrara (2009) for the euro area and by Chen et al. (2011) for the US in order to anticipate recessions. Yet, our study differs from these works in three ways. First, we use the factor-augmented framework to replicate the business cycles without any forecasting perspectives. Second, we use this model in order to analyze the specific role of financial variables by opposition to standard macroeconomic data, such as industrial production, that are generally used to assess business cycles in a coincident manner. Third, we compare two dynamic factor estimation methods, namely the static approach of Stock and Watson (2002) and the dynamic approach put forward by Doz et al. (2011) and we show that the dynamic alternative provides more accurate results in terms of business cycle replication.

The paper is organized as follows: Section 2 presents the model and Section 3 contains the details of the application analyzing the euro area business cycle over the period January 1974–December 2008.

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2. Modeling

2.1. Factor models

Assume that we observe a vector of n stationary zero mean time series $x_t = [x_{1t}, \ldots, x_{nt}]'$, for $t = 1, \ldots, T$, where n is large. The objective of dynamic factor modeling is to decompose $(x_t)_t$ into a sum of two mutually orthogonal unobservable components: a common component of low dimension $(\chi_t)_t$, summarizing the dynamics common to all the series, and an idiosyncratic component $(\xi_t)_t$, specific to each series. The common component $(\chi_t)_t$ is supposed to linearly summarize the common behavior of the n series. For $t = 1, \ldots, T$, the static factor model is defined by

$$x_t = \Lambda f_t + \xi_{t,} \tag{1}$$

where Λ is the loading matrix of dimension $(n \times r)$, 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 $f_t = [f_{1t}, \ldots f_{rt}]$, and $\xi_t = [\xi_{1t}, \ldots, \xi_{nt}]'$ is a vector of n idiosyncratic mutually uncorrelated components, driven by variable-specific shocks.

To take dynamics into account in modeling, an alternative specification integrates explicitly the dynamics of the factors f_t. Specifically the dynamic factor representation is supposed to be given by the following equation

$$x_t = A(L) f_t + \xi_t, \tag{2}$$

where the common component $\chi_t = A(L) f_t$ integrates a linear dynamics where $A(L)$ is a $(n \times r)$ matrix describing the autoregressive form of the r factors. If we assume that there exists a $(n \times q)$ matrix $B(L)$ such that $B(L) = A(L)N(L)$ with $N(L)$ of dimension $(r \times q)$, then the dynamic factor is such that $f_t = N(L)U_t$ where U_t is a $(q \times 1)$ independent vector containing the dynamic shocks. It follows that the factor dynamics are described by

$$A(L) f_t = B(L) U_t, \tag{3}$$

which specifies a VAR model for the factor f_t.

2.2. Binary response model

We assume now 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 $(r_t)_t$ stem from a latent continuous variable, denoted $(y_t)_t$, defined by the following general linear equation, for all t,

$$y_t = \alpha + \beta'_0 f_t + \ldots + \beta'_k f_{t-k} + \varepsilon_t, \tag{4}$$

where for $j = 0, \ldots, k$, $f_{t-j} = (f_{1,t-j}, \ldots, f_{r,t-j})'$ is a r-vector of lagged dynamic factors used as explanatory variables, $\beta_j = (\beta_j^1, \ldots, \beta_j^r)'$ is a r-vector parameter and $(\varepsilon_t)_t$ is the error term supposed to be a strong white noise process with finite variance σ_ε^2.

The binary response modeling relies on the following relationship between $(r_t)_t$ and $(y_t)_t$

$$r_t = \begin{cases} 1 & \text{if } y_t \le 0, \\ 0 & \text{if } y_t > 0 \end{cases} \tag{5}$$

For each date t, it can be easily proved that the conditional probability of recession is given by

$$P(r_t = 1 | I_t) = F\left(-\alpha - \beta'_0 f_t - \ldots - \beta'_k f_{t-k}\right), \tag{6}$$

where I_t represents the large informational set available at date t and $F(.)$ is the cumulative density function of $(\varepsilon_t)_t$. We assume here that the distribution of $(\varepsilon_t)_t$ is supposed to be Gaussian in order to get the probit specification of the model (the logit specification is obtained when $F(.)$ is the logistic function). We define the model described by Eqs. (1) to (6) as a *factor-augmented probit* model.

2.3. Parameter estimation

Parameter estimation of the factor-augmented probit model is carried out using a two-step procedure. First, dynamic factors $\left(\hat{f}_t\right)_t$ are estimated, then those estimated factors are introduced in Eq. (4) in order to estimate the conditional probability of being in recession given in Eq. (6). Note that this two-step procedure implicitly incorporates the uncertainty inherent to the measure of factors. However, Bai and Ng (2008) prove that, asymptotically, the estimated factors do not affect parameter estimates $\hat{\beta}_j$ in Eq. (6). Regarding factor estimation in the static framework of Eq. (1), we implement the procedure of Stock and Watson (2002) using static principal component analysis (PCA) to estimate the factors, denoted $\hat{f}_t^{sta}$. An eigenvalue decomposition of the empirically estimated covariance matrix, $T^{-1} \sum_{t=1}^{T} x_t x'_t$, provides the $(n \times r)$ eigenvector matrix $\hat{S} = \left(\hat{S}_1, \ldots, \hat{S}_r\right)$ containing the eigenvectors $\hat{S}_j$ corresponding to the r largest eigenvalues for $j = 1, \ldots, r$. The factor estimates are the first r principal components of x_t defined as $\hat{f}_t^{sta} = \hat{S}' x_t$.

In the dynamic framework of Eq. (2), factor estimation is carried out by using a 2-step Kalman filter to compute ML estimates as proposed by Doz et al. (2011). This approach consists in estimating first the parameters by PCA, then, in the second step, the model is put into a state-space form and factors are estimated via Kalman smoothing. We note $\hat{f}_t^{dyn}$ the estimated factors.

2.4. Specification and validation

The choice of the number of static factors r to include in Eq. (4) is determined by using the Bai and Ng (2002) test. This test determines the optimal number of factors by minimizing a penalized information criterion.[1] Note that Bai and Ng (2002) propose a variety of information criteria that vary according to the penalization function. When dealing with dynamic factors, Bai and Ng (2007) put forward a similar test enabling to account for dynamics in the factors.

To assess the goodness-of-fit of binary response models, we implement first the $Pseudo-R^2$ measure proposed by Estrella (1998) such as

$$Pseudo{-}R^2 = 1 - \frac{L_u}{L_c}^{-(2/n)L_c} \tag{8}$$

where L_u is the log-likelihood of the considered model and L_c is the log-likelihood of a reference nested model to which L_u is compared. By construction, the nested model must have a lower log-likelihood value than the basic model. This $Pseudo-R^2$ measure is often used in the literature for comparison between models (see for example Estrella et al., 2003).

We also decide to focus on a general goodness-of-fit criterion to assess the quality of the models, often used in business cycle analysis (see, among others, Anas et al., 2008), namely the quadratic probability score (QPS) given by

$$QPS = \frac{1}{T} \sum_{t=1}^{T} \left(r_t - \hat{P}\left(r_t = 1 \middle| I_t\right)\right)^2, \tag{9}$$

[1] We implement the version of the test that determines r by minimizing a penalized information criterion:

$$IC(k) = \ln[V(k,F)] + k \times \left(\frac{n+T}{nT}\right) \ln\left(\frac{nT}{n+T}\right),$$

where $V(r,F)$ is the sum of squared residuals such that: $V(k,F) = (nT)^{-1} \sum_{i=1}^{n} \sum_{t=1}^{T} (x_{it} - \Lambda f_t)^2$.