Economics Letters 145 (2016) 83–87

Contents lists available at ScienceDirect

Economics Letters

journal homepage: www.elsevier.com/locate/ecolet

Measuring financial cycles in a model-based analysis: Empirical evidence for the United States and the euro area

Gabriele Galati [a,*], Irma Hindrayanto [a], Siem Jan Koopman [b,c], Marente Vlekke [d]

[a] De Nederlandsche Bank, Amsterdam, The Netherlands
[b] Vrije Universiteit Amsterdam, The Netherlands
[c] CREATES, Aarhus University, Denmark
[d] Centraal Planbureau, Den Haag, The Netherlands

HIGHLIGHTS

- Financial cycles are estimated with an unobserved components time series model.
- The credit-to-GDP ratio (or total credit) and house prices share similar medium-term cycles.
- Financial cycles are longer and have larger amplitudes compared to business cycles.
- The length and amplitude of financial cycles varies across countries and over time.

ARTICLE INFO

Article history:
Received 19 April 2016
Received in revised form
27 May 2016
Accepted 31 May 2016
Available online 7 June 2016

JEL classification:
C22
C32
E30
E50
E51
G01

Keywords:
Unobserved component time series model
Kalman filter
Maximum likelihood estimation
Band-pass filter
Medium-term cycles

ABSTRACT

We adopt an unobserved components time series model to extract financial cycles for the United States and the five largest euro area countries over the period 1970–2014. We find that financial cycles can parsimoniously be estimated by house prices and total credit or the credit-to-GDP ratio. We show that these medium-term cycles are longer and have larger amplitudes than business cycles, and that their length and amplitude vary over time and across countries.

1. Introduction

We explore a new approach to the measurement of financial cycles, and examine their main characteristics for the United States, Germany, France, Italy, Spain and the Netherlands. The financial cycle captures systematic patterns in the financial system that can have important macroeconomic consequences (Borio et al., 2001). In recent years, several methods to measure the financial cycle have been proposed. These include variations of the Burns and Mitchell (1946) turning-point analysis, (e.g. Claessens et al., 2011, 2012) and non-parametric bandpass filters (e.g. Aikman et al., 2015 and Schüler et al., 2015). Igan et al. (2009) and Hiebert et al. (2014) are among the papers that apply both approaches with the aim of reaching more robust conclusions. The financial cycle is typically characterized by the co-movement of medium-term cycles in credit, the credit-to-GDP ratio and house prices; its peaks tend to coincide with onsets of financial crises (Drehmann et al., 2012).

* Corresponding author.
E-mail address: e.b.g.galati@dnb.nl (G. Galati).

http://dx.doi.org/10.1016/j.econlet.2016.05.034
0165-1765/

We consider a new approach to extracting financial cycles based on a multivariate unobserved components time series model (UCTSM) for these three variables, see Harvey and Koopman (1997). The model is based on a joint decomposition of the three time series into long-term trends, and combinations of short- and medium-term cycles. We investigate whether the cycles for the individual series have the same frequencies and dynamic persistencies. While this approach has been applied extensively to business cycle analysis, see Valle e Azevedo et al. (2006) and references therein, there are only a few illustrations for financial variables, of which Koopman and Lucas (2005) and Chen et al. (2012) are examples. In comparison to non-parametric filters, we do not need prior assumptions on the length of the cycle, which is particularly convenient for our exploratory research on the financial cycle. Moreover, our model-based analysis relies on diagnostic statistics to investigate whether the model and the estimated trends and cycles are accurate and reliable.

2. Data and modeling approach

We extract financial cycles from quarterly time series of credit, the credit-to-GDP ratio and house prices for the United States (US), Germany, France, Italy, Spain and the Netherlands, over the sample period from 1970 to 2014; the data sets are similar to the ones used in Drehmann et al. (2012). In our analysis, we have considered two definitions for credit: total credit and bank credit. We only present a selection of the results for total credit, all other results are available upon request from the authors. The time series are taken from the macroeconomic database of the Bank of International Settlements; they are deflated by the consumer price index and logarithms are taken except for the credit-to-GDP ratio.

We follow the steps in the analysis of Koopman and Lucas (2005): first we extract cycles from all time series based on an univariate UCTSM, and second, we verify whether the cycles in a multivariate UCTSM share common characteristics. Standard likelihood ratio tests are adopted to establish whether 'similar' cycles exist in the financial variables under consideration for the US and the five euro area (EA) countries.

2.1. Unobserved components time series models

The observation vector of our three variables at time t is denoted by y_t, for $t = 1, \ldots, T$. The UCTSM in our study is formulated by a trend-cycle decomposition model for each variable equation i, that is

$$y_{it} = \mu_{it} + \psi_{it} + \varepsilon_{it}, \quad \varepsilon_{it} \overset{i.i.d.}{\sim} \mathcal{N}(0, \sigma^2_{\varepsilon,i}), \; i = 1, \ldots, N, \tag{1}$$

where y_{it} is the ith element of y_t, μ_{it} represents the *trend* component, ψ_{it} represents the short- to medium-term *cycle* dynamics, and ε_{it} is the *irregular* that is normally distributed, with mean zero and variance $\sigma^2_{\varepsilon,i}$, and serially independent. The three components are unobserved. The trend associated with one variable is seemingly unrelated with the trends of the other two variables. This also applies to the cycle and the irregular. However, the covariances between the disturbances driving a particular component are typically non-zero and imply a dependence structure amongst the three variables and their dynamic characteristics.

A key part of the analysis is to determine the appropriate smoothness of the trend component, that is how much dynamic fluctuation in the variable y_{it} is assigned to the trend as opposed to the cycle. In terms of the m-order trend model of Harvey and Trimbur (2003), we determine the smoothness by the choice of m in the trend specification $\mu_{it} = \mu_{it}^{(m_i)}$, with

$$\begin{aligned} \mu^{(k)}_{i,t+1} &= \mu^{(k)}_{it} + \mu^{(k-1)}_{it}, \quad k = m_i, m_i - 1, \ldots, 2, \\ \mu^{(1)}_{i,t+1} &= \mu^{(1)}_{it} + \zeta_{it}, \quad \zeta_{it} \overset{i.i.d.}{\sim} \mathcal{N}(0, \sigma^2_{\zeta,i}), \end{aligned} \tag{2}$$

where ζ_{it} is the disturbance that drives the trends μ_{it}, and where covariance (ζ_{it}, ζ_{jt}) can be non-zero for $i \neq j$. In a frequency-domain analysis, a higher value for m implies that the low-pass gain function will have a sharper cutoff. Hence the trend component becomes smoother as m increases. When $m = 2$, the trend reduces to an integrated random walk process. Notice that Eq. (2) implies $\Delta^m \mu^{(m)}_{i,t+1} = \zeta_{it}$. For many macroeconomic time series, m is typically set to 2; see, for example, Valle e Azevedo et al. (2006). This choice for m is also adopted for the financial variables business failure rates and credit spreads in Koopman and Lucas (2005).

The cycle component ψ_{it} has the stochastic dynamic specification proposed by Harvey (1989) and is given by

$$\begin{pmatrix} \psi_{i,t+1} \\ \psi^{(*)}_{i,t+1} \end{pmatrix} = \phi_i \begin{bmatrix} \cos\lambda_i & \sin\lambda_i \\ -\sin\lambda_i & \cos\lambda_i \end{bmatrix} \begin{pmatrix} \psi_{it} \\ \psi^{(*)}_{it} \end{pmatrix} + \begin{pmatrix} \omega_{it} \\ \omega^{(*)}_{it} \end{pmatrix}, \quad \begin{pmatrix} \omega_{it} \\ \omega^{(*)}_{it} \end{pmatrix} \overset{i.i.d.}{\sim} \mathcal{N}(0, \sigma^2_{\omega,i} I_2), \tag{3}$$

where the frequency λ_i is measured in radians, $0 \leq \lambda_i \leq \pi$, and the persistence ϕ_i is the damping factor, $0 < \phi_i < 1$, for $i = 1, \ldots, N$. The period or length of the stochastic cycle ψ_{it} is given by $2\pi/\lambda_i$. The cycle ψ_{it} is a stationary dynamic process. The disturbances $(\omega_{it}, \omega^{(*)}_{it})'$ drive the cyclical stochastic process and may be correlated with $(\omega_{jt}, \omega^{(*)}_{jt})'$, for $i \neq j$. All irregular, trend and cycle disturbances are serially and mutually uncorrelated, at all times and lags, but individually they can be correlated with their counterparts of the other two variables. The model is complete with appropriate initial conditions for trend $\mu_{i,1}$ and cycle $\psi_{i,1}$ as discussed in Durbin and Koopman (2012).

2.2. Similar trends and cycles

In our analysis, we investigate whether the trends and cycles can be treated as *similar* trends and cycles. In case of the trend, we verify whether the trend order m_i can be the same m, for $i = 1, \ldots, N$. In case of the cycle, we verify whether the frequency λ_i and persistence ϕ_i can have respectively the same values for $i = 1, \ldots, N$. However, the scales of trends and cycles, as determined by the variances and covariances of the disturbances driving the components, can still be different under these 'similar' restrictions. The implications for the properties of similar cycles, both in the time- and frequency-domain analyses, are discussed in Harvey and Koopman (1997). Standard likelihood ratio tests can be used to verify whether the frequency and persistency parameters are equal amongst equations, after they are estimated from univariate UCTSMs.

2.3. State space methodology

Univariate and multivariate UCTSMs can be formulated in the general linear state space model as given by the *observation equation* $y_t = Z\alpha_t + \varepsilon_t$, with state vector α_t, and the *state updating equation* $\alpha_{t+1} = T\alpha_t + \eta_t$, where Z and T are system matrices that determine the dynamic properties of y_t, and, together with the variance matrices for ε_t and η_t, contain the static parameters of the model. The state vector contains the unobserved components μ_t and ψ_t, together with auxiliary variables such as $\mu_t^{(k)}$, for $k = 1, \ldots, m-1$, and $\psi_t^{(*)}$ in Eqs. (2) and (3). The various disturbances are placed in an appropriate manner in the vectors ε_t and η_t. Further details of the trend-cycle model in state space form are provided by Harvey (1989).

Once the model is represented in state space form, the Kalman filter and related state space methods can be applied. We estimate the unknown static parameters by the method of maximum likelihood; numerical maximization requires the Kalman filter to