Short-term forecasting of business cycle turning points: *a mixed-frequency Markov-switching dynamic factor model analysis*

Siem Jan Koopman [1] Matías Pacce [2]

[1] VU University of Amsterdam, Timbergen Institute Amsterdam and CREATES, Aarhus University

[2] BBVA Research and University of Alicante

June 3, 2016

Index

Motivation

- An accurate and promptly evaluation about the current and the short-run future economic situation is a highly valuable information for policy makers and private-agents.

  It becomes even worthier when the question is about anticipating an upcoming economic recession.

- Predicting recession in real-time is not an easy task. As Hamilton (2011) pointed out:

  "*... the dating of business cycle turning points [...] on a real-time basis is a bigger challenge than many academics might assume, due to factors such as data revisions and changes in economic relationships over time.*"

Business Cycle characterization - DFMs

- Two key features of the business cycles (Burns and Mitchel, 1946)

  1) Co-movements among economic series.

     Stock and Watson (1989, 1991, 1993): Dynamic factor model able to capture unobserved co-movements between economic time series

  2) Non-linear behaviour of the economy between recession and expansion periods

     Hamilton (1989): Univariate two-state regime Markov-switching model for the evolution of the GDP

⇒ Both in one model (Diebold and Rudebusch, 1996):

Chauvet (1998) and Kim and Nelson (1998) through multivariate dynamic factor Markov-switching (DFMS) models

Mixed-frequencies DFMs

- Why not to account for the GDP when characterizing the cycle?

$\Rightarrow$ Mixing-frequencies

- Within a linear framework
  - Mariano and Murasawa (2003), Camacho and Perez-Quiros (2010), Blasques et al. (2017) (among many others)
- Within a non-linear framework
  - Camacho, Perez-Quiros and Poncela (2012)

Our contribution

- We develop a Bayesian analysis for the nowcasting and forecasting of turning points in the business cycle using mixed-frequency DF models (latent factors subject to switching means).
- The key novelty on the analysis is our model-based treatment of the dynamic in a mixed-frequency data set (we base on the stacked approach of Blasques et al., 2014).
- Following Camacho et al. (2012) our specification also allows for ragged-ends (given its importance when real-time estimations).
- Our easily handle Bayesian approach to the mixed-frequency DF models also applies for the linear-case

Empirical application - US recession probabilities and forecast

- Gains when including GDP to compute in-sample recession probabilities are small (similar to Camacho et al., 2012)
- Base on Chauvet and Piger (2008) we analyze the real-time business cycles dating performance of our model
  - Enlarging the model by using GDP significantly improves the real-time estimates of turning points when the target is to obtain the NBER recession dates, with more impact on the peak's date identification
  - There are no gains on the date of announcements of turning points when adding GDP data
  - Using latest available information means, in general, the announcement of a turning-point one month in advance
- We also evaluate our model's forecast performance.
  - Compared with other methodologies, better nowcast accuracy when at least one month of monthly data from the current quarter is already released (i.e. during the 2^{nd} and 3^{rd} month of the quarter).

Single-index DFMS model

Following Kim and Nelson (1998), we represent co-movements among economic variables and business cycle asymmetries within a single model.

$$\Delta y_{it} \quad = \quad \beta_i(L)\Delta f_t + u_{it} \qquad\qquad i = 1, \dots, n \qquad (1)$$

Business cycles shifts are introduced as a switching mean on the factor. Therefore, the dynamics of the model is given by,

$$\Phi_f(L)\left(\Delta f_t - \mu_{s_t}\right) \quad = \quad \eta_t \qquad\qquad \eta_t \overset{iid}{\sim} N\left(0, \sigma_\eta^2\right) \qquad (2)$$

$$\Phi_i(L)u_t^i \quad = \quad \epsilon_{it} \qquad\qquad \epsilon_{it} \overset{iid}{\sim} N\left(0, \sigma_i^2\right) \qquad (3)$$

where η_t and ϵ_{it} are independent of each other for all t and i. The two states of the economy evolves according to a Markov-switching process:

$$\mu_{s_t} \quad = \quad \mu_0 + \mu_1 S_t \qquad\qquad \mu_1 > 0\,,\ S_t = \{0, 1\}$$

$$p_{ij} \quad = \quad Pr[S_t = j | S_{t-1} = i] \qquad\qquad \sum_{j=1}^{2} p_{ij} = 1 \quad \forall i$$

Stacked approach - Blasques,et al (2017)

Monthly variables x_τ^m can be stacked into a quarterly observed vector (x_t^q) of the form,

$$x_t^q = \begin{pmatrix} x_{t,1}^q \\ x_{t,2}^q \\ x_{t,3}^q \end{pmatrix} = \begin{pmatrix} x_{3(t-1)+1}^m \\ x_{3(t-1)+2}^m \\ x_{3(t-1)+3}^m \end{pmatrix} \tag{4}$$

where $x_{t,i}^q$ is the i-th element of x_t^q, where t refers to the quarter the monthly observation belong to and i indicates the month within the t quarter.

Consider an AR(1) of the form $x_{t,1} = \phi x_{t-1,3} + \varepsilon_{t,1}$, then it is possible to write

$$\begin{pmatrix} x_{t,1}^q \\ x_{t,2}^q \\ x_{t,3}^q \end{pmatrix} = \begin{pmatrix} 0 & 0 & \phi \\ 0 & 0 & \phi^2 \\ 0 & 0 & \phi^3 \end{pmatrix} \begin{pmatrix} x_{t-1,1}^q \\ x_{t-1,2}^q \\ x_{t-1,3}^q \end{pmatrix} + \begin{pmatrix} 1 & 0 & 0 \\ \phi & 1 & 0 \\ \phi^2 & \phi & 1 \end{pmatrix} \begin{pmatrix} \epsilon_{t,1}^q \\ \epsilon_{t,2}^q \\ \epsilon_{t,3}^q \end{pmatrix}$$

Example: replacing $x_{t,1}$ in $x_{t,2}$

$$x_{t,2} = \phi^2 x_{t-1,3} + \phi\varepsilon_{t,1} + \varepsilon_{t,2}$$

Stacked approach for DFMS models

Assuming a monthly observable variable which dynamics is explained by the model described in equations (1)-(3), the process can be described as,

$$\Delta x_\tau^m = \beta_x \Delta f_\tau^m + \epsilon_\tau^m \quad (5)$$

$$\Phi_f(L)\left(\Delta f_\tau^m - \mu_{s_\tau}^m\right) = \eta_\tau^m \quad (6)$$

where $\epsilon_\tau^m \overset{iid}{\sim} N\left(0, \sigma_x^2\right)$ and $\eta_\tau \overset{iid}{\sim} N\left(0, \sigma_f^2\right)$. Adding a quarterly variable Δy_t which also depends on Δf_τ^m and using the stacked vector representation (4) for the unobserved common factor, $\Delta f_t^q = \left(\Delta f_{t,1}^q \quad \Delta f_{t,2}^q \quad \Delta f_{t,3}^q\right)'$, it is possible to write

$$\begin{aligned} \Delta y_t &= \beta_y \Delta f_{3t-2}^m + \beta_y \Delta f_{3t-1}^m + \beta_y \Delta f_{3t}^m + \xi_t \\ &= \left(\beta_y \quad \beta_y \quad \beta_y\right) \Delta f_t^q + \xi_t \quad (7) \end{aligned}$$

where $\xi_t \overset{iid}{\sim} N\left(0, \sigma_\xi^2\right)$.

Stacked approach for DFMS models

Under the state space representation of (5)-(7) and assuming an AR(1) process for the factor for exposition reasons:

$$\begin{aligned} x_t &= Z\alpha_t + \epsilon_t & \epsilon_t &\sim N(0, H) \\ \alpha_{t+1} &= M_{s_t} + T\alpha_t + R\eta_t & \eta_t &\sim N(0, Q) \end{aligned} \tag{8}$$

where

$$x_t = \begin{pmatrix} y_t & x^q_{t,1} & x^q_{t,2} & x^q_{t,3} \end{pmatrix}' \qquad \alpha_t = \begin{pmatrix} f^q_{t,1} & f^q_{t,2} & f^q_{t,3} \end{pmatrix}'$$

$$\epsilon_t = \begin{pmatrix} \xi_t & \epsilon^m_{t,1} & \epsilon^m_{t,2} & \epsilon^m_{t,3} \end{pmatrix}' \qquad \eta_t = \begin{pmatrix} \eta^q_{t,1} & \eta^q_{t,2} & \eta^q_{t,3} \end{pmatrix}'$$

$$Z = \begin{pmatrix} \beta_y & \beta_y & \beta_y \\ \beta_x & 0 & 0 \\ 0 & \beta_x & 0 \\ 0 & 0 & \beta_x \end{pmatrix} \qquad M_{s_t} = \begin{pmatrix} (1-\phi_f L)\mu^q_{s_{t,1}} \\ (1-\phi_f^2 L^2)\mu^q_{s_{t,2}} \\ (1-\phi_f^3 L^3)\mu^q_{s_{t,3}} \end{pmatrix}$$

$$T = \begin{pmatrix} 0 & 0 & \phi_f \\ 0 & 0 & \phi_f^2 \\ 0 & 0 & \phi_f^3 \end{pmatrix} \qquad R = \begin{pmatrix} 1 & 0 & 0 \\ \phi_f & 1 & 0 \\ \phi_f^2 & \phi_f & 1 \end{pmatrix}$$

$$H = \text{diag}\left(\sigma^2_\xi, \sigma^2_\epsilon, \sigma^2_\epsilon, \sigma^2_\epsilon\right) \qquad Q = 1$$

Estimation Strategy

- The basic estimation procedure relies on Kim and Nelson (1998) (Bayesian inference). In particular, MH algorithm within Gibbs sampling:

    1) The unobserved common factor is drawn conditional on the states and parameters (simulation smoother algorithm as proposed by Carter and Kohn, 1994).
    2) The states $(S_1, \dots, S_T)$ are generated conditional on the unobserved common component and all parameters (multi-move Gibbs-Sampling algorithm)
    3) Conditional on the common factor and unobserved states, equations from (5)-(7) are independent, allowing for a separate treatment of each other.

- The identification assumption for the model stands on assuming the variance of the common unobserved component (σ_f) to be equal to one.

Sampling parameters related to quarterly variables

Sampling parameters associated with quarterly variables (β_y, σ_y):

$$\begin{aligned} \Delta y_t &= \begin{pmatrix} \beta_y & \beta_y & \beta_y \end{pmatrix} \Delta f_t^q + u_{y,t} \qquad (9) \\ u_{y,t} &= \phi_{1,y} u_{y,t-1} + \ldots + \phi_{p,y} u_{y,t-p} + \xi_t \end{aligned}$$

For monthly variables: pre-whitening and conjugate normal prior,

$$(1 - \Phi_x L)\Delta x_{t,1} = (1 - \Phi_x L)\beta_x \Delta f_{t,1} + \epsilon_{t,1}$$

With quarterly variables (using stacked approach) is exactly the same. Pre-multiply both sides of equation (9) by $(\Phi_y = 1 - \phi_y L)$ to obtain,

$$(1 - \phi_y L)\Delta y_t = \begin{pmatrix} \beta_y & \beta_y & \beta_y \end{pmatrix} \begin{pmatrix} (1 - \phi_y L)\Delta f_{t,1}^q \\ (1 - \phi_y L)\Delta f_{t,2}^q \\ (1 - \phi_y L)\Delta f_{t,3}^q \end{pmatrix} + \xi_t \qquad (10)$$

Different from equation (9), equation (10) has uncorrelated residuals, allowing for the possibility of using a Normal-gamma conjugate prior for the estimation of β_y and σ_y. Note that $L\Delta f_{t,1}^q = \Delta f_{t-1,1}^q$.

Other approaches - Camacho et al. (2012)

Camacho et al. (2012) based on Mariano and Murasawa (2003) for their DFMS model. In particular,

$$\Delta y_t^q = \frac{1}{3}\Delta f_t^m + \frac{2}{3}\Delta f_{t-1}^m + \Delta f_{t-2}^m + \frac{2}{3}\Delta f_{t-3}^m + \frac{1}{3}\Delta f_{t-4}^m \tag{11}$$

Main shortcoming: when estimated through the approximate maximum-likelihood method a total of 2^5 different paths need to be considered at each t in the most simpler case (equation (2) replaced by a switching intercept $\Delta f_t = \mu_{s_t} + \eta_t$)

The authors proposed to approximate the density of Δy_t^q by,

$$f\left(\Delta y_t^q\right) = \sum_{j=1}^{32} \pi_j^* f\left(\Delta y_t^q | s_t^* = j\right) \approx \sum_{i=1}^{2} \pi_i f\left(\Delta y_t^q | s_t = i\right)$$

Through a Monte Carlo study they showed small effects when the idiosyncratic variance of the quarterly indicator is high enough.

Setting up the stacked approach the number of path needed to be estimated is reduced to 2^3 in the most simpler case (even though we don't need it when based on Bayesian estimation).

Other approaches - Marcellino et al (2016)

Marcellino, Porqueddu and Venditti (2016) also based on Mariano and Murasawa (2003) for a Bayesian estimation of a mixed-frequency DF model with stochastic volatility. In their approach equation (7) becomes:

$$\begin{aligned}\Delta y_t &= +\frac{1}{3}\beta_y\Delta f_t + \frac{2}{3}\beta_y\Delta f_{t-1} + \beta_y\Delta f_{t-2} + \frac{2}{3}\beta_y\Delta f_{t-3} + \frac{1}{3}\beta_y\Delta f_{t-4} + \\ &\quad \frac{1}{3}u_{y,t} + \frac{2}{3}u_{y,t-1} + u_{y,t-2} + \frac{2}{3}u_{y,t-3} + \frac{1}{3}u_{y,t-4}\end{aligned}$$

Marcellino et al. (2016) note that two main difficulties appear to estimate β_y.

1) Two missing observations every quarter (solved by using only true observations for the estimation).
2) A MA(4) appears in the equation, where the error (u_t) follows an AR(p) process (they propose to work out the variance covariance matrix of the error term, Θ, and pre-multiply both sides of the equation by $\Theta^{-\frac{1}{2}}$ in order to obtain a standard regression with uncorrelated residuals).

In-sample analysis: US case

- We base on Kim and Nelson (1998) monthly specification of a DFMS model adapting it to deal with mixing frequencies under the stacked approach
- Five variables included: GDP, industrial production (IP), real personal income less transfer payments (INC), real manufacturing and trade industry sales (SLS) and employees on non-agricultural payrolls (EMP)
- Data sample is from January 1959 to September 2014.
- AR(2) for factor and idiosyncratic components. Since payroll employment could be a lagging indicator we included three lags of f_t in the payroll equation (as in Stock and Watson, 1989 and Kim and Nelson, 1998)
- "Compact" state-space representation (quasi-difference equations)
- Priors selected are quite diffuse. For all β is $N(0, 1000)$, for σ is $IG = (6; .0001)$, while for AR polynomials is set equal to $N(0, \Sigma)$, where $\Sigma = [1 \quad 0\ ;\ 0 \quad .5]$. For ($\mu_0$ and μ_1) is $N(0, I_2)$. Following Kim and Nelson (1998) informative priors are used for transition probabilities.

Estimated Parameters

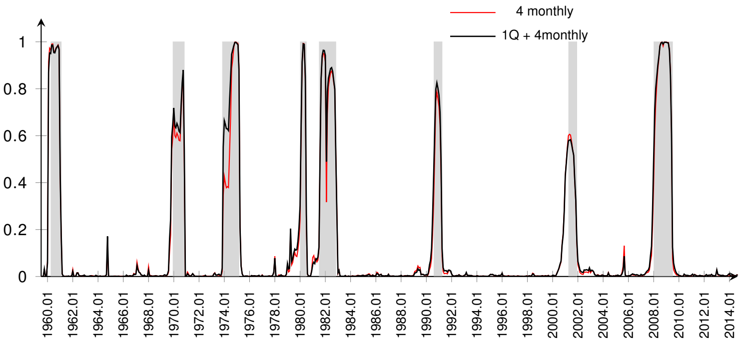
1 Quarterly and 4 monthly variables included								
Param	IP	INC	SLS	EMP	GDP	Factor		
β	.485	.184	.412	.094	.197			
	[0.466; 0.503]	[0.173; 0.195]	[0.394; 0.429]	[0.089; 0.099]	[0.187; 0.207]			
ϕ_1^i	−.067	−.199	−.414	.097	−.218	.224		
	[−0.109; −0.027]	[−0.226; −0.173]	[−0.442; −0.384]	[0.068; 0.127]	[−0.269; −0.167]	[0.182; 0.272]		
ϕ_2^i	−.113	−.076	−.208	.379	−.044	.188		
	[−0.149; −0.077]	[−0.103; −0.049]	[−0.236; −0.179]	[0.349; 0.41]	[−0.097; 0.009]	[0.144; 0.235]		
σ_i^2	.188	.274	.533	.015	.304	1.000		
	[0.175; 0.201]	[0.263; 0.284]	[0.509; 0.555]	[0.014; 0.016]	[0.281; 0.325]			
	μ_0	μ_1	$\mu_0 + \mu_1$	q	p	β_2^{EMP}	β_3^{EMP}	β_4^{EMP}
	−1.934	2.213	0.279	0.871	0.981	.014	.014	.025
	[−2.128; −1.749]	[2.029; 2.415]	[0.219; 0.343]	[0.844; 0.906]	[0.976; 0.986]	[0.009; 0.019]	[0.01; 0.018]	[0.021; 0.029]

4 monthly variables included								
Param	IP	INC	SLS	EMP	GDP	Factor		
β	.501	.183	.421	.091	–			
	[0.482; 0.519]	[0.171; 0.194]	[0.403; 0.439]	[0.087; 0.096]	–			
ϕ_1^i	−.088	−.190	−.418	.109	–	.219		
	[−0.132; −0.046]	[−0.217; −0.162]	[−0.446; −0.388]	[0.08; 0.138]	–	[0.177; 0.266]		
ϕ_2^i	−.109	−.066	−.213	.391	–	.157		
	[−0.147; −0.071]	[−0.094; −0.04]	[−0.241; −0.184]	[0.362; 0.421]	–	[0.112; 0.204]		
σ_i^2	.170	.277	.527	.016	–	1.000		
	[0.156; 0.183]	[0.266; 0.287]	[0.504; 0.549]	[0.015; 0.016]	–			
	μ_0	μ_1	$\mu_0 + \mu_1$	q	p	β_2^{EMP}	β_3^{EMP}	β_4^{EMP}
	−1.971	2.24	0.269	0.861	0.98	.015	.015	.026
	[−2.161; −1.784]	[2.058; 2.435]	[0.21; 0.331]	[0.832; 0.898]	[0.976; 0.986]	[0.01; 0.02]	[0.011; 0.019]	[0.022; 0.003]

Note: Values showed are the median and the 75(within brackets) from the posterior distribution. In both cases, the first 10000 draws in the Gibbs simulation were discarded, while the next 40000 draws were used for the estimation

In-sample US smoothed recession probabilities

Figure: Mixing vs. non-mixing frequency models



Note: Both alternatives are computed using 40000 draws in the Gibss simulation (after discarding the first 10000 draws.

Estimating Turning Points in real-time

- Our data sets includes data vintages from January 1977 to September 2014
- Data release varies depending on the variable:
  - EMP, IP and INC (one lag), SLS (two lags), GDP (at the end of the month following the end of the quarter)
- Different days for publications. We assume we are at the last day of the month (as in Chauvet and Piger, 2008)
- Camacho et al. (2012) show that allowing for ragged-ends in order to use the latest available information helps to improve the inference about the current state of the cycle.
- Our strategy to deal with the unbalanced panel rely on skipping missing observations for the updating Kalman filter equations of the simulation smoother algorithm.

Revised versus latest available data

- Different from the classical model, having a balanced panel in our stacking approach means having all the information within a quarter
- To understand the importance of using the latest available information, we also consider the probabilities estimated with the same amount of information Chauvet and Piger (2008) use at each t (waiting for the second release of three of the monthly variables). We call it using “revised data”.
- When including the GDP, “revised data” also means not using the advanced estimates for that variable (following Hamilton, 2010).

Turning point decision rule - Chauvet and Piger (2008)

(3) Peak date

(2) First probability below .5

	Jan 1991	Feb 1991
Jun-90	0.09	0.09
Jul-90	0.34	0.36
Aug-90	0.55	0.59
Sep-90	0.73	0.79
Oct-90	0.88	0.95
Nov-90	0.90	0.98
Dec-90	0.77	0.97
Jan-91		0.92

Note: Recession probabilities using mixing frequencies and non-revised data

(1) Three consecutive probabilities over .8

For trough dates, three consecutive probabilities below .2 and look for the first above .5 prior to those values.

Turning points dates: NBER and estimations

RECESSIONS					
PEAK DATE AS DETERMINED BY:					
NBER	Chauvet & Piger (2008)	Mixing Freq (revised data)	Mixing Freq (latest data)	Non-Mixing Freq (revised data)	Non-Mixing Freq (latest data)
Jan 1980(Q2)	Jan 1980	Jan 1980	Jan 1980	Jan 1980	Jan 1980
Jul 1981(Q3)	Aug 1981	Jul 1981	Jul 1981	Aug 1981	Aug 1981
Jul 1990(Q3)	Jul 1990	Jul 1990	Jul 1990	Jul 1990	Jul 1990
Mar 2001(Q1)	Jan 2001	Dec 2000	Dec 2000	Nov 2000	Dec 2000
Dec 2007(Q4)	Feb 2008*	Jan 2008	Jan 2008	Feb 2008	Feb 2008

EXPANSION					
TROUGH DATE AS DETERMINED BY:					
NBER	Chauvet & Piger (2008)	Mixing Freq (revised data)	Mixing Freq (latest data)	Non-Mixing Freq (revised data)	Non-Mixing Freq (latest data)
Jul 1980(Q3)	Jun 1980	Jun 1980	Jun 1980	Jun 1980	Jun 1980
Nov 1982(Q4)	Oct 1982	Oct 1982	Nov 1982	Oct 1982	Oct 1982
Mar 1991(Q1)	Mar 1991	Mar 1991	Mar 1991	Mar 1991	Mar 1991
Nov 2001(Q4)	Nov 2001	Nov 2001	Nov 2001	Nov 2001	Nov 2001
Jun 2009(Q2)	Jul 2009*	Jun 2009	Jun 2009	Jun 2009	Jun 2009

Note: * Values taken from Hamilton (2011).

Turning points announcement dates: NBER and estimations

RECESSIONS

PEAK DECLARATION DATE AS ANNOUNCED BY:

NBER	Chauvet & Piger (2008)	Mixing Freq (revised data)	Mixing Freq (latest data)	Non-Mixing Freq (revised data)	Non-Mixing Freq (latest data)
Jun 3, 1980	Jul 1980	Jul 1980	Jun 1980	Jul 1980	Jun 1980
Jan 6, 1982	Feb 1982	Feb 1982	Jan 1982	Feb 1982	Jan 1982
Apr 25, 1991	Feb 1991	Feb 1991	Feb 1991	Feb 1991	Feb 1991
Nov 26, 2001	Jan 2002	Dec 2001	Nov 2001	Dec 2001	Nov 2001
Dec 1, 2008	Jan 2009*	Nov 2008	Oct 2008	Nov 2008	Oct 2008

EXPANSION

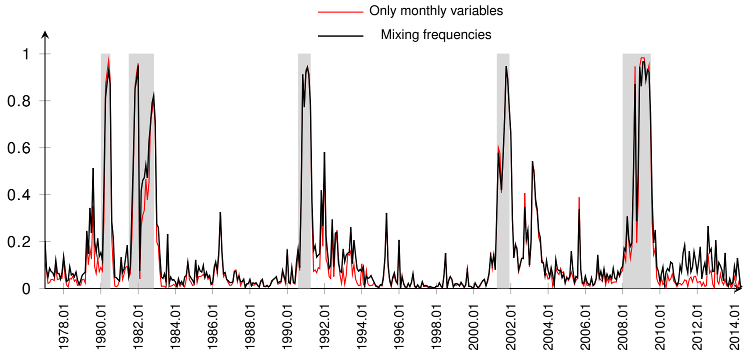
TROUGH DECLARATION DATE AS ANNOUNCED BY:

NBER	Chauvet & Piger (2008)	Mixing Freq (revised data)	Mixing Freq (latest data)	Non-Mixing Freq (revised data)	Non-Mixing Freq (latest data)
Jul 8, 1981	Dec 1980	Dec 1980	Nov 1980	Dec 1980	Nov 1980
Jan 8, 1983	May 1983	May 1983	Apr 1983	May 1983	Apr 1983
Dec 22, 1992	Sep 1991	Aug 1991	Aug 1991	Aug 1991	Jul 1991
Jul 17, 2003	Aug 2002	Aug 2002	Jun 2002	Aug 2002	Jul 2002
Sep 20, 2010	Jan 2010	Jan 2010	Dec 2009	Nov 2009	Nov 2009

Note: * Values taken from Hamilton (2011).

Real-time US smoothed recession probabilities

Figure: Mixing vs. non-mixing frequency models



Note: Both alternatives were computed at each t using 8000 draws in the Gibss simulation (after discarding the first 2000 draws). Latest available information is always used.

Nowcasting

Chauvet and Potter (2012) compare 13 different models in terms of forecast accuracy and found differences in predicting output during recession and expansion phases (real-time analysis).

AR(2) + unobserved common component + switching-states probabilities $\Rightarrow$ it is possible to do it significantly better than a simple AR(2) and all other 13 models there studied (but is a two step estimation)

The stacking approach gives us the opportunity of directly analyze the forecast accuracy for the GDP when a mixed frequencies DFMS is used.

Nowcasting accuracy (1977.Q1 to 2013.Q4 vintages)

	Models	RSME Full Sample	RSME Expansion	RSME Recession	Theil Inequality Total	Bias	Var	Cov
Forecast at the 3rd month of each quarter	AR(2)	2.634	2.121	4.536	.387	.014	.418	.574
	Relative	1.00	1.00	1.00	1.00			
	AR(2) - DFMS	2.198	1.788	3.747	.313	.016	.259	.732
	Relative	.834***	.843***	.826**	.809			
	MF - DFMS	1.900	1.801	2.365	.261	.041	.169	.797
	Relative	.722***	.849**	.521**	.674			
Forecast at the 2nd month of each quarter	AR(2)	2.627	2.131	4.483	.386	.014	.425	.567
	Relative	1.00	1.00	1.00	1.00			
	MF - DFMS	2.204	1.943	3.287	.297	.086	.184	.733
	Relative	.839**	.911	.733*	.768			
Forecast at the 1st month of each quarter	AR(2)	2.626	2.117	4.519	.389	.011	.442	.554
	Relative	1.00	1.00	1.00	1.00			
	MF - DFMS	2.661	2.271	4.208	.352	.108	.167	.731
	Relative	1.014	1.073	.931	.906			

Note: AR(2)-DFMS refers to the augmented AR(2) model proposed by Chauvet and Potter (2012). MF-DFMS refers to the mixing-frequency DFMS model. (*), (**) and (***) refers to a 10%, 5% and a 1% statistically significant difference relative to the AR(2) model. In the case of the AR(2)-DFMS we use Clark and McCracken (2005) test for nested models. For the MF-DFMS model we employ the corrected Diebold and Mariano (2002) test.

Conclusions

- We propose an alternative way of estimating mixed frequency DFMS models
- We introduce an easily handle way of estimating mixing-frequencies DF models through Bayesian methods
- No gains when including GDP to compute in-sample recession probabilities or for the date of announcements of turning points
- Adding the GDP does it better gains when the target are the NBER turning points
- Using latest available information means an earlier announcement of turning-points
- Improvements in nowcast accuracy when at least one month of monthly data from the current quarter is already released

THANK YOU FOR THE ATTENTION