Short-term macroeconomic forecasting and turning point detection after the Great Recession[1]

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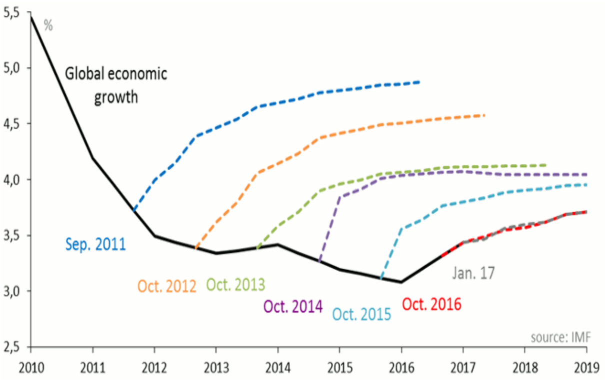
[1] The views expressed here are those of the authors and do not necessarily reflect those of the Banque de France or the OECD

Global GDP forecasts after the GFC: Not far from a complete disaster ...



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- Over-heating before the GFC and *mean reversion* property
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- Decline in productivity ...

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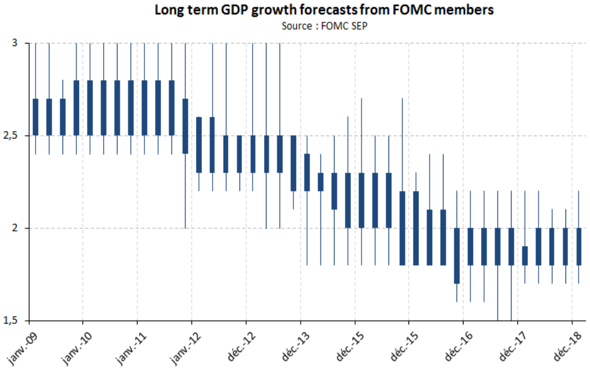
and 2 stylized facts in advanced economies of major importance for forecasters:

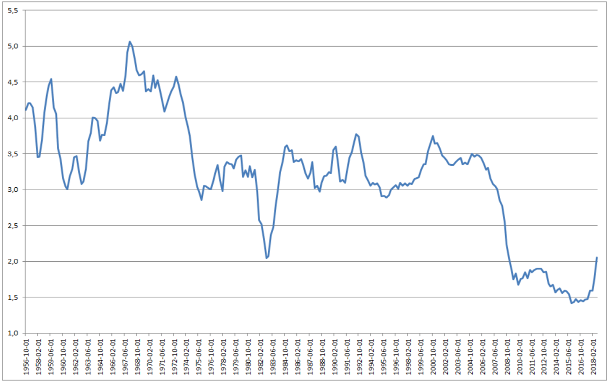
1. Long-term declining trend in GDP
2. Higher macro volatility

SF1: Decline in long-term US GDP after GFC



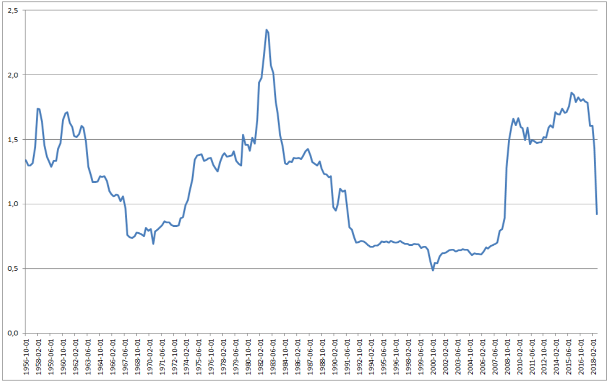
SF1: In fact, a secular decline in US GDP trend

Rolling average over 10 years for US GDP growth



SF2: Increasing macro volat after the Great Moderation

Rolling coefficient of variation over 10 years for US GDP growth



Objectives of this paper

- Put forward a new small-scale Markov-Switching Dynamic Factor Model (MS-DFM) for the US accounting for:
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- Real-time assessment of the extended MS-DFM for both TP detection and GDP forecasting

Main results

- Evidence of a gain in goodness-of-fit from using our **Extended MS-DFM** compared with linear DFM, specially when accounting for a switch in variance during the *Great Moderation*
- Match the NBER dating of turning points but send a real-time signal in advance with a 6 months lead for peaks and 12 months lead for troughs
- Improve GDP forecasting accuracy by 10% for $h = 6$ months
- The *Great Recession* doesn't bring the *Great Moderation* to an end
- Loss of about 1pp in long-run GDP growth since 2000, about 0.5pp since the *Great Recession*

Related literature

- MS-DFM: Small-scale DFM with changes in growth regimes (Diebold and Rudebusch (ReStat, 1996), Kim and Nelson (ReStat, 1998))
- Univariate MS with both changes on growth and volatility regimes (McConnell and Perez-Quiros (AER, 2000), Bai and Wang (JAE, 2011))
- Integration of time-varying trend in GDP:
  - Eo and Kim (ReStat, 2016): Univariate case with MS changes in growth
  - Giordani, Kohn and van Dijk (JoE, 2007): Univariate case with both MS changes on growth and volatility regimes
  - Antolin-Diaz, Drechsel and Petrella (ReStat, 2017): Multivariate DFM with Stochastic Volatility (but no MS changes in growth)

Related literature

	Multivariate framework (factor model)	**Markov-Switching on Intercept**	**Markov-Switching on the volatility of shocks**	**Stochastic volatility**	**Time-varying long-term GDP growth rate**
Antolin-Diaz *et al.* (2017)	X			X	X
Bai and Wang (2011)		X	X		
Diebold and Rudebusch (1996)	X	X			
Eo and Kim (2016)		X			X
Giordani *et al.* (2007)[3]		X	X		X
Kim and Nelson (1998)	X	X			
Marcellino *et al.* (2016)	X			X	
McConnell and Perez-Quiros (2000)		X	X		
This paper	**X**	**X**	**X**		**X**

Model specification

Let assume we observe y_{it} macro variables, $i = 1, \ldots, n$ (n small)

- **Measurement equation**

$$\Delta y_{it} = a_{it} + \gamma_i \Delta c_t + u_{it}$$

$$\text{where: } \begin{cases} \Delta y_{it} : \text{demeaned growth rate of variable } i \\ a_{it} : \text{deviation from mean growth rate} \\ \Delta c_t : \text{common factor} \end{cases}$$

- **State equations**

$$\begin{cases} a_{i,t} = a_{i,t-1} + \sigma_{a_i}.\nu_t^{a_i} & ; \quad \nu_t^{a_i} \sim \mathbb{N}(0,1) \\ \Phi(L)\Delta c_t = \mu_{S_t,V_t} + \sqrt{1 + hV_t}.\sigma_c.\nu_t^c & ; \quad \nu_t^c \sim \mathbb{N}(0,1) \\ \Psi_i(L)u_{it} = \sigma_i.\varepsilon_{it} & ; \quad \varepsilon_{it} \sim \mathbb{N}(0,1) \end{cases}$$

Model specification

- S_t and V_t are independent Markov chains with 2 regimes:

$$\begin{cases} S_t = 0 : \textit{economic expansion}; & S_t = 1 : \textit{economic recession} \\ V_t = 0 : \textit{low volatility} \quad ; & V_t = 1 : \textit{high volatility} \end{cases}$$

and

$$\begin{cases} P(S_t = 0 | S_{t-1} = 0) = PS_{00} \ ; & P(S_t = 1 | S_{t-1} = 1) = PS_{11} \\ P(V_t = 0 | V_{t-1} = 0) = PV_{00}; & P(V_t = 1 | V_{t-1} = 1) = PV_{11} \end{cases}$$

- Variance of the state equation governing factor dynamics:

$$\begin{cases} Variance = \sigma_c^2 \quad ; & \text{in the low volatility regime} \\ Variance = (1+h)\sigma_c^2; & \text{in the high volatility regime}(h > 0) \end{cases}$$

Model specification

- Intercept of the state equation governing factor dynamics:

$$\mu_{S_t,V_t} = \mu_{00} + \mu_{01} V_t + \mu_{10} S_t + \mu_{11} S_t V_t$$

with

$$\begin{cases} \mu_{00} & = \text{ low volatility/recession regime} \\ \mu_{00} + \mu_{01} & = \text{ high volatility/recession regime} \\ \mu_{00} + \mu_{10} & = \text{ low volatility/expansion regime} \\ \mu_{00} + \mu_{01} + \mu_{10} + \mu_{11} & = \text{ high volatility/expansion regime} \end{cases}$$

Model specification

- We want to include both Monthly (IPI, sales, personal income, employment) and Quarterly GDP in the model.
- How to deal with mixed frequencies? Rewrite the measurement equations by approximating quarterly GDP as a weighted average of current and past monthly GDP values

$$\begin{aligned}\Delta y_{1t}^{q} = & \frac{1}{3}a_{1,t}^{q} + \frac{2}{3}a_{1,t-1}^{q} + a_{1,t-2}^{q} + \frac{2}{3}a_{1,t-3}^{q} + \frac{1}{3}a_{1,t-4}^{q} \\ + & \gamma_1^q\left(\frac{1}{3}\Delta c_t + \frac{2}{3}\Delta c_{t-1} + \Delta c_{t-2} + \frac{2}{3}\Delta c_{t-3} + \frac{1}{3}\Delta c_{t-4}\right) \\ + & \frac{1}{3}u_{1,t}^{q} + \frac{2}{3}u_{1,t-1}^{q} + u_{1,t-2}^{q} + \frac{2}{3}u_{1,t-3}^{q} + \frac{1}{3}u_{1,t-4}^{q}\end{aligned}$$

and

$$\Delta y_{jt}^{m} = a_{jt}^{m} + \gamma_j^m(L)\Delta c_t + u_{jt}^{m}$$

Model specification: State-space representation

- Measurement equations of the monthly variables, $j = 1, \ldots, 4$, are pre-multiplied by the lag polynomial characterising residual autocorrelation:

$$\Psi_j^m(L)\Delta y_{jt}^m = \Delta y_{jt}^{m,*} = \gamma_j^m(L)\Psi_j^m(L)\Delta c_t + \sigma_j^m.\varepsilon_{jt}^m, \qquad \varepsilon_{jt}^m \sim \mathbb{N}(0,1)$$

$$\underbrace{\begin{pmatrix} \Delta y_{1t}^q \\ \Delta y_{1t}^{m,*} \\ \Delta y_{2t}^{m,*} \\ \Delta y_{3t}^{m,*} \\ \Delta y_{4t}^{m,*} \end{pmatrix}}_{\equiv \Delta y_t} = \underbrace{\begin{pmatrix} \frac{1}{3} & \frac{2}{3} & 1 & \frac{2}{3} & \frac{1}{3} & \frac{\gamma_{10}^q}{3} & \frac{2\cdot\gamma_{10}^q}{3} & \gamma_{10}^q & \frac{2\cdot\gamma_{10}^q}{3} & \frac{\gamma_{10}^q}{3} & 0 & \frac{1}{3} & \frac{2}{3} & 1 & \frac{2}{3} & \frac{1}{3} \\ 0 & 0 & 0 & 0 & 0 & \gamma_{10}^{m,*} & \gamma_{11}^{m,*} & \gamma_{12}^{m,*} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \gamma_{20}^{m,*} & \gamma_{21}^{m,*} & \gamma_{22}^{m,*} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \gamma_{30}^{m,*} & \gamma_{31}^{m,*} & \gamma_{32}^{m,*} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \gamma_{40}^{m,*} & \gamma_{41}^{m,*} & \gamma_{42}^{m,*} & \gamma_{43}^{m,*} & \gamma_{44}^{m,*} & \gamma_{45}^{m,*} & 0 & 0 & 0 & 0 & 0 \end{pmatrix}}_{\equiv Z} \begin{pmatrix} a_t \\ a_{t-1} \\ a_{t-2} \\ a_{t-3} \\ a_{t-4} \\ \Delta c_t \\ \Delta c_{t-1} \\ \Delta c_{t-2} \\ \Delta c_{t-3} \\ \Delta c_{t-4} \\ \Delta c_{t-5} \\ u_{1,t}^q \\ u_{1,t-1}^q \\ u_{1,t-2}^q \\ u_{1,t-3}^q \\ u_{1,t-4}^q \end{pmatrix} + \begin{pmatrix} 0 \\ \sigma_1^m \cdot \varepsilon_{1t}^m \\ \sigma_2^m \cdot \varepsilon_{2t}^m \\ \sigma_3^m \cdot \varepsilon_{3t}^m \\ \sigma_4^m \cdot \varepsilon_{4t}^m \end{pmatrix}$$

Bayesian estimation strategy

- Gibbs sampling with consecutive steps to draw the underlying state vector, the Markov variables $S_{1\dots T}$ and $V_{1\dots T}$, and the other constant model parameters (loading coefficients for the state vector, autoregressive parameters. variances, etc.).
- Main advantages of the Bayesian estimation: (1) modular (easy to add or remove building blocks), and (2) simplifies the inference on $S_{1\dots T}$ and $V_{1\dots T}$ because the state vector can be considered as an observed variable in the corresponding Gibbs sampling steps.
- Draws from the state vector (which includes the non-stationary time-varying GDP growth rate): sequential Kalman filter/smoother with diffuse initialisation [Koopman and Durbin (2000, 2003)], then simulation smoother introduced by Durbin and Koopman (2002).

Estimation results

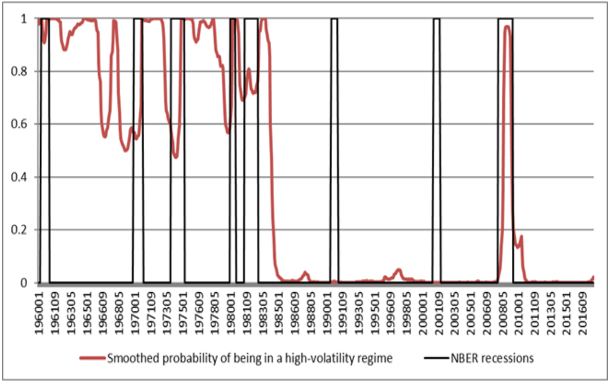
- Estimation sample: 1960m01-2017m12
- We assume that only GDP presents a time-varying trend captured by $a^q_{1,t}$ ($a^m_{j,t} = 0$ for $j = 1, \ldots, 4$)
- Parameter estimation:

	$\hat{\mu}_{S_t,V_t}$	95% CI	Expectation knowing $\hat{\phi}_1$
Low Volat / Recession	-0.19	[-0.32, -0.07]	-0.26
High Volat / Recession	-0.46	[-0.77, -0.26]	-0.64
Low Volat / Expansion	0.02	[0.00, 0.04]	0.02
High Volat / Expansion	0.14	[0.06, 0.24]	0.20

- Stronger impact of volatility during recessions than during expansions

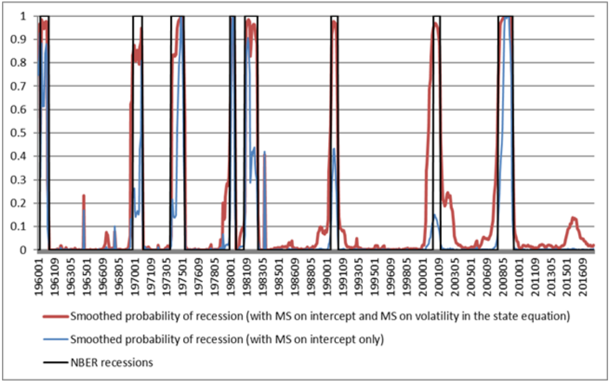
Probability of being in high-volat regime

- The *Great Recession* doesn't imply the end of the *Great Moderation* (Charles, Darne, Ferrara, EcoInq, 2018)



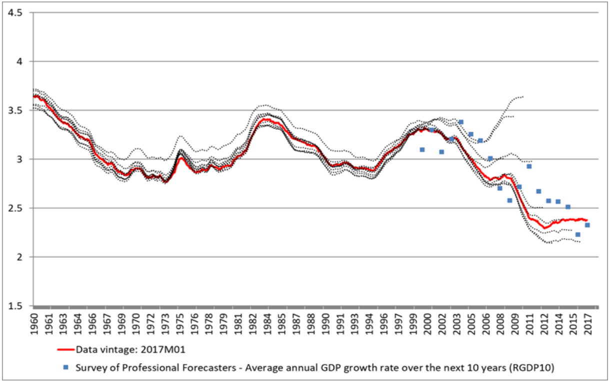
Probability of being in recession

- Switches in volat help to capture recessions during the *Great Moderation*



Long-term decline in US GDP growth

- Loss in long-run GDP growth is about 1pp since 2000 (about 0.5pp since GR)



Ranking of various models: DIC

- Deviance Information Criteria (DIC) well designed to compare models within a Bayesian framework
- Easy to compute when estimation based on Bayesian MCMC techniques, but need to pay attention to the number of variables in the conditioning set for accurate inference
- Here, computation of the conditional log-likelihood from the Kalman filter step $f(Y_t|\theta, Y_{t-1,\dots,1})$ (using $E(\alpha_t|Y_{t-1,\dots,1})$ and $V(\alpha_t|Y_{t-1,\dots,1})$), thus allowing to remove the large state vector from the conditioning set.
- DIC is given by:

$$DIC = \{E_{\theta|Y}(-2\log f(Y|\theta))\} + \{E_{\theta|Y}(-2\log f(Y|\theta)) + 2\log f(Y|\tilde{\theta})\}$$

where $\theta = (S_{1,\dots,T}, V_{1,\dots,T}, \dots)$ and $\tilde{\theta}$ is the posterior mean of θ.

Ranking of various models: DIC

- DIC computations:

Model specification	DIC
Linear DFM	3924.1
MS-DFM with MS on Intercept only	3866.6
MS-DFM with MS on Intercept and Volatility	3671.2
MS-DFM with MS on Intercept and Volatility, and time-variation in long-term GDP growth rate	3672.6

- Both MS features, especially MS on volatility, reduce the DIC as compared to a linear DFM.
- The inclusion of time-variation in the long-term GDP growth rate only marginally affects the DIC, but GDP is only 1 out of 5 observed variables and is only available every 3 months. Focusing on GDP forecasting performance may lead to a different conclusion.

Real-time detection of turning points since 2000

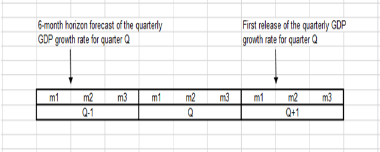
- Identification of peaks and troughs using a simple rule based on a threshold
- Dates of peaks and troughs are in line with NBER Business Cycle Dating Committee
- A lead in announcement dates by about 6 months for peaks and 12 months for troughs (only 2 events)

Peak date		Announcement date		Difference
NBER BCDC	Extended MS-DFM	NBER BCDC	Extended MS-DFM	
2001m03	2000m08	2011m11	2001m05	-6
2007m12	2007m11	2008m12	2008m05	-7

Trough date		Announcement date		Difference
NBER BCDC	Extended MS-DFM	NBER BCDC	Extended MS-DFM	
2001m11	2001m12	2003m07	2002m04	-15
2009m06	2009m06	2010m09	2009m12	-9

Real-time GDP forecasts

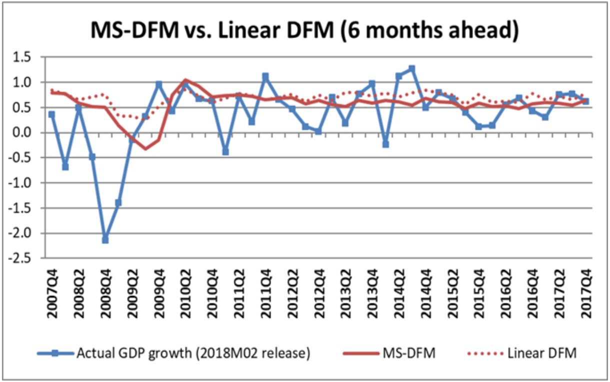
- Calendar of the forecasting exercise:



- Relative RMSFEs of the Extended MS-DFM vs Linear DFM: Improvement by about 10% by accounting for changes in growth and volatility regimes for longer horizons

	m-1	m-2	m-3	m-4	m-5	m-6
2007q4-2017q4	1.01	1.01	1.04	0.95	0.96	0.96
2007q4-2009q2	1.03	1.02	1.07	0.91	0.91	0.91
2012q1-2017q4	0.98	0.94	0.92	0.96	0.90	0.91

Real-time GDP forecasts over 2007-2017



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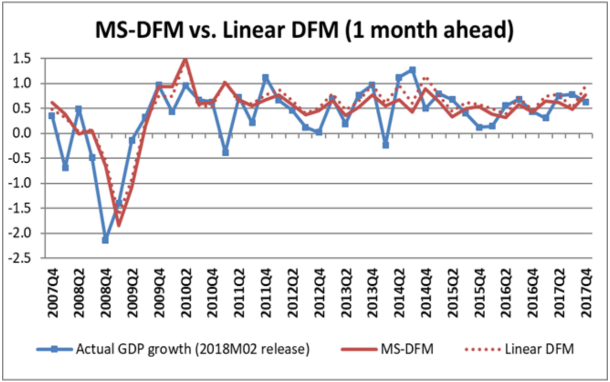

Conclusions

- The introduction of Markov-Switching volatility in the standard MS-DFM improves the detection of turning points during the Great Moderation and is supported by the DIC
- Adding MS features and allowing for time-variation in long-term GDP growth increases the timeliness of turning points detection, without undermining the reliability
- Adding MS features and allowing for time-variation in long-term GDP growth improves short-term real-time forecasting performance during and after the Great Recession, as compared to a linear DFM
- The Great Recession is not the end of the Great Moderation
- Evidence of slowdown in long-run US GDP growth since 2000 (loss of about 1pp, half of this loss since the Great Recession