Monthly measures for the level and uncertainty of the US economy

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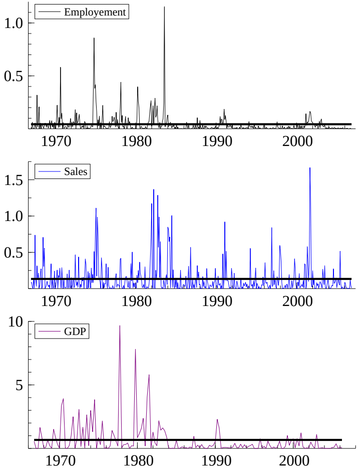
Motivation

- ✓ Timely information on the state of the economy is of paramount importance for economic policy decision making: both in terms of the level of the economy and its fluctuations.
- ✓ These two measures are estimated considering a monthly coincident index and its variance by using indicators of economic activity.
- ✓ The model is based on mixed frequency (monthly and quarterly) and as product the monthly GDP is estimated by disaggregation of the quarterly values. Policy implications $\Rightarrow$ can be used to help in the intra quarterly decision making and for nowcast and forecast.
- ✓ The estimated volatility, expressed as a variance conditional on past square errors of several key economic indicators, allows the surveillance and the investigation on the determinants of the fluctuations of the economy.
- ✓ Finally, the time varying model for the variance produces correct confidence intervals in GDP forecasts, which are wider (tighter) as the uncertainty in the economy increase (decrease).

Stylized fact

Most of US economic variables experiment a decline in the volatility with a break in the fluctuations in the mid 80s (also in Stock and Watson (2002)).



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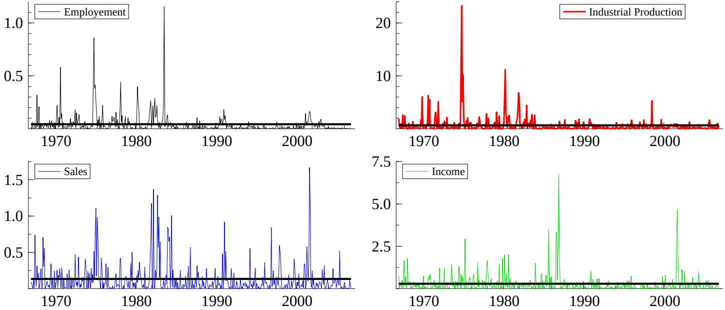

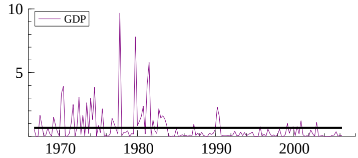

Variances

	1968−2006	before 1985	after 1985
Employment	0.043	0.075	0.019
Industrial production	0.664	1.109	0.321
Sales	0.133	0.159	0.114
Income	0.282	0.283	0.267
GDP(Q)	0.676	1.263	0.231

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Background literature

High frequency GDP & Coincident Index: Stock & Watson (1991, 2002), Forni *et al* (2000) Chow & Lin (1971), Harvey & Chung (2000), Moauro & Savio (2005), Proietti & Moauro (2006), Evans(2005), Giannone *et al.*(2007) Mariano & Murasawa (2003)

Great Moderation & Conditional Volatility Stock & Watson (2006), Cecchetti *et al.*(2006), Cogley & Sargent (2005), Primiceri (2005), Sims & Zha (2005), Reichlin *et al.* (2008)

We built a bridge between the two approaches estimating the level (Monthly GDP and coincident index) and the fluctuations (volatility and Great moderation) of the economy.

Outline

- ✓ Motivation
- ✓ Stylized facts and literature
- ✓ The model

  Which model for volatility...?
  ...Multiples regimes Garch
- ✓ Results for US economy

  Surveillance of uncertainty in the economy
  Monthly GDP and forecast
- ✓ Discussion about the date of the great moderation
- ✓ Conclusion and future agenda

The Dynamic Factor Model with volatility

$\mathbf{y}_t$ is $N \times 1$ vector of monthly and quarterly series, $I(1)$, resulting from the linear combination of a common cyclical trend (denoted by μ_t)and idiosyncratic components ($\boldsymbol{\mu}_t^*$) specific for each series

$$\mathbf{y}_t = \underbrace{\boldsymbol{\vartheta}_0 \mu_t + \boldsymbol{\vartheta}_1 \mu_{t-1}} + \underbrace{\boldsymbol{\mu}_t^*} + \mathbf{X}_t \beta.$$

- common index: $(1 - \phi L)\Delta \mu_t = \eta_t$
- Idiosyncratic: $\mathbf{D}(L)\Delta \boldsymbol{\mu}_t^* = \delta + \boldsymbol{\eta}_t^*$, where $\mathbf{D}(L)$ is a diagonal polynomial matrix.

The disturbances $\eta_t \sim \text{NID}(0, \sigma_t^2)$ and $\boldsymbol{\eta}_t^* \sim \text{NID}(\mathbf{0}, \sigma_t^2 \boldsymbol{\Sigma}_{\eta^*})$ are mutually uncorrelated at all leads and lags and $\Sigma_{\eta^*} = \text{diag}(\sigma^2_{\eta_1^*}, \ldots, \sigma^2_{\eta_N^*})$ is the time constant matrix of variances of the idiosyncratic specific components.
$\mathbf{X}_t$= exogenous variables for calendar effects and intervention variables (level shifts, additive outliers, etc.).

Which model for the Volatility...?

1. Stock & Watson (2002), a variance mechanism with two regimes, prior and after the great moderation, but does not capture the conditional heteroskedasticity found in the data

2. SV model as in Priminceri (2005) and Stock & Watson(2006): difficult to estimate in our framework (mixed frequency) it requires Importance sampling or MCMC and not feasible the link with the fluctuations of the indicators

3. Harvey, Ruiz and Sentana (1991): GARCH model for unobserved components; appealing econometrics but it lacks of economic meaning

4. As indicator of the underlying volatility that drives the economy, it should be caused, in some sense, by the fluctuations of the macroeconomic indicators. We propose a Garch-type model accounting for idiosyncratics.

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VOLINX (σ_t^2) the volatility of the economy follows a GARCH-type model:

$$\sigma_t^2 = (1 - \alpha_0 - \alpha_1) + \alpha_0 \sigma_{t-1}^2 + \alpha_1 \sum_{i=1}^{N} \omega_i v_{i(t-1)}^2; \;\; 0 \leq \alpha_0 < 1, \alpha_1 \geq 0$$

α_0: accounts for persistency

α_1: accounts for shocks novelty: linear combination of past square errors of the idiosyncratic components of each economic indicator.

v_{it}: vector of standardized innovations of the Kalman filter, $v_{it} = (y_{it} - \mathrm{E}(y_{it}|\mathbf{y}_1, \ldots, \mathbf{y}_{t-1}))$, previsions standardized errors conditional to the current Information set.

ω_i: weights of the linear combination, estimated endogenously, show which are the most relevant variables that explain the volatility of the economy (similar to the approach for the loadings of the level of the coincident index).

Multiples regimes Garch

- ✓ A previous application of this model suggests a change in the level of the unconditional variance around 1984.
- ✓ The literature on the great moderation discusses extensively, without fully conclusive answer, about the starting date and the type of the change, whereas it was a break rather than a declining patter.
- ✓ A feasible and suitable formalization might be a GARCH-type model with multiple regimes for the unconditional variance.

$$\sigma_t^2 = \varpi_1 I_{[1]} + \varpi_2 I_{[2]} + \alpha_0 \sigma_{t-1}^2 + \alpha_1 \sum_{i=1}^{N} \omega_i v_{i(t-1)}^2$$

$I_{[1]}$ ($I_{[2]}$) indicator function prior (posterior) great moderation
$\varpi_2 < \varpi_1 \Rightarrow$ decrease in volatility after the great moderation
$\varpi_1 > 0$, $\varpi_2 > 0$, $0 \leq \alpha_0 < 1$, $\alpha_1 \geq 0$, $\omega_i > 0$,$\sum_{i=1}^{N} \omega_i = 1$.

State Space Form

- The coincident index $(1-\phi L)\Delta\mu_t = \eta_t$ can be written as

$$\begin{aligned}\Delta\mu_t &= g_t,\\ g_t &= \phi g_{t-1} + \sigma_t^2\eta_t,\end{aligned}$$

and the Markovian representation of the model for μ_t becomes

$$\begin{aligned}\mu_t &= [1,0]\,\alpha_{\mu,t}\\ \alpha_{\mu,t} &= \mathbf{T}_\mu\alpha_{\mu,t-1} + [1,1]'\,\sigma_t^2\eta_t,\quad \mathbf{T}_\mu = \begin{bmatrix} 1 & \phi \\ 0 & \phi \end{bmatrix}\end{aligned}$$

- A similar representation holds for each individual μ_{it}^*, with ϕ_j replaced by d_{ij}, so that, if we assume that

$$\begin{aligned}\mu_{it}^\star &= [1,0]\,\alpha_{\mu i,t}\\ \alpha_{\mu i,t} &= \mathbf{T_i}\alpha_{\mu i,t-1} + [\delta_i,\delta_i]' + [1,1]'\,\sigma_t^2\eta_{it}^\star,\quad \mathbf{T_i} = \begin{bmatrix} 1 & d_i \\ 0 & d_i \end{bmatrix},\end{aligned}$$

where δ_i is the drift of the $i-th$ idiosyncratic component, and thus of the series.

- Combining all the blocks, we obtain the SSF of the complete model by defining the state vector α_t, with dimension $2+2N$, where N is the number of indicators, as follows:

$$\alpha_t = [\alpha'_{\mu,t}, \alpha'_{\mu_1,t}, \ldots, \alpha'_{\mu_N,t}]'. \tag{1}$$

- The measurement and the transition equations of the S&W model in levels are:

$$\mathbf{y}_t = \mathbf{Z}\alpha_t + \mathbf{X}_t\beta, \quad \alpha_t = \mathbf{T}\alpha_{t-1} + \mathbf{W}\beta + \mathbf{H}\varepsilon_t, \tag{2}$$

where $\varepsilon_t = [\eta_t, \eta^*_{1,t}, \ldots, \eta^*_{N,t}]'$ and the system matrices are given below:

$$\mathbf{Z} = \left[\theta_0, \vdots\, \theta_1 \ \vdots\, \mathrm{diag}(e_2', \ldots, e_2') \right], \qquad \mathbf{T} = \mathrm{diag}(\mathbf{T}_\mu, \mathbf{T}_1, \ldots, \mathbf{T}_N), \tag{3}$$
$$\mathbf{H} = \mathrm{diag}(h_\mu, h_1, \ldots, h_N).$$

where $e_k' = [1, 0, \ldots, 0]$ is a $1xk$ vector and $h_\mu, \ldots, h_N = [1, 1]$

- The SSF is complete with the equation for the GARCH-type volatility:

$$\sigma_t^2 = \varpi_1 I_{[1]} + \varpi_2 I_{[2]} + \alpha_0 \sigma_{t-1}^2 + \alpha_1 \sum_{i=1}^{N} \omega_i v_{it-1}^2$$

where $I_{[1]}$ ($I_{[2]}$) indicator function prior (posterior) great moderation and $\varpi_1 > 0$, $\varpi_2 > 0$, $0 \leq \alpha_0 < 1$, $\alpha_1 \geq 0$, $\omega_i > 0$, $\sum_{i=1}^{N} \omega_i = 1$.

Disaggregation in time

We follow Harvey (1989) and Proietti(2006) Let us partitioning the set of indicators, $\mathbf{y}_t$, into two groups, $\mathbf{y}_t = [\mathbf{y}'_{1,t}, \mathbf{y}'_{2,t}]'$, of dimension $N = (N1+N2)$, where $\mathbf{y}_{1,t}$ contains the series observable every period (monthly) and the second block the series partially observable (quarterly).

- We consider an underlying random sequence $\mathbf{y}^*_{2,t}$ such that $\ln(\mathbf{y}_{2,\tau}) = \frac{1}{3}\sum_{i=0}^{2}\ln(\mathbf{y}^*_{2,3\tau-i}), \quad \tau = 1,2,\ldots,[T/3]$. or $\mathbf{y}_{2,t}$ is the geometric mean of the unobserved three monthly values $\mathbf{y}^*_{2,t-1}, \mathbf{y}^*_{2,t-2}, \mathbf{y}^*_{2,t-3}$. Then define a $N_2 \times 1$ vector $\mathbf{y}^c_{2,t}$, as follows

$$\mathbf{y}^c_{2,t} \quad = \quad \psi_t \mathbf{y}^c_{2,t-1} + \frac{1}{3}\ln(\mathbf{y}^*_{2,t})$$

where ψ_t is the cumulator variable, defined by: $\psi_t = \begin{cases} 0 & t = 3(\tau-1)+1, \quad \tau = 1,\ldots,[n/3] \\ 1 & \text{otherwise .} \end{cases}$ In other words the cumulator is equal to the (observed) aggregated series at times $t = 3\tau$, and otherwise it contains the partial cumulative monthly underlying value $\frac{1}{3}\ln(\mathbf{y}^*_{2,t})$ making up the quarter, up to and including the current one. The monthly GDP in logarithms is obtained from $\mathbf{y}^*_{2,t}$ applying an inverse function which is linear.
The original SSF is augmented by $\mathbf{y}^c_{2,t}$, which is observed at times $t = 3\tau, \tau = 1,2,\ldots,[n/3]$, and is missing at intermediate times:

$$\alpha^*_t = \begin{bmatrix} \alpha_t \\ \mathbf{y}^c_{2,t} \end{bmatrix}, \quad \mathbf{y}^\dagger_t = \begin{bmatrix} \mathbf{y}_{1,t} \\ \mathbf{y}^c_{2,t} \end{bmatrix}$$

- The final measurement and transition equations are as follows:

$$\mathbf{y}^\dagger_t = \mathbf{Z}^*\alpha^*_t + \mathbf{X}_t\beta, \quad \alpha^*_t = \mathbf{T}^*\alpha^*_{t-1} + \mathbf{W}^*\beta + \mathbf{H}^*\varepsilon_t, \tag{4}$$

with system matrices:

$$\mathbf{Z}^* = \begin{bmatrix} \mathbf{Z}_1 & \mathbf{0} \\ \mathbf{0} & \mathbf{I}_{N_2} \end{bmatrix}, \quad \mathbf{T}^* = \begin{bmatrix} \mathbf{T} & \mathbf{0} \\ \mathbf{Z}_2\mathbf{T} & \psi_t \mathbf{I} \end{bmatrix}, \quad \mathbf{W}^* = \begin{bmatrix} \mathbf{W} \\ \mathbf{Z}_2\mathbf{W} + \mathbf{X}_2 \end{bmatrix}, \quad \mathbf{H}^* = \begin{bmatrix} \mathbf{I} \\ \mathbf{Z}_2 \end{bmatrix}\mathbf{H}. \tag{5}$$

where $\mathbf{Z}_2$ is the block of the measurement matrix $\mathbf{Z}$ corresponding to the second set of variables (the cumulator for the quarterly GDP), $\mathbf{Z} = [\mathbf{Z}'_1, \ \mathbf{Z}'_2]'$ and $\mathbf{y}_{2,t} = \mathbf{Z}_2\alpha_t + \mathbf{X}_2\beta$, where we have partitioned $\mathbf{X}_t = [\mathbf{X}'_1 \ \ \mathbf{X}'_2]'$.

Estimation and time constraint procedure

The estimation procedure and the disaggregation of the quarterly GDP is as in Proietti(2006) (also applied for the Eurostat project of the Monthly GDP of the Euro Area, see Frale, Marcellino, Mazzi and Proietti(2008)).

- The model involves mixed frequency data, e.g. monthly indicators and quarterly GDP. Following Harvey (1989) and Proietti(2006), the state vector in the SSF is suitably augmented by using an appropriately defined cumulator variable in order to traslate the time constraint into a problem of missing observations.
- In our analysis the series in the model are expressed in logarithms, therefore to deal with a linear constraint we follow the approximation suggested by Mariano and Murasawa (2003, 2004) to disaggregate the quarterly log GDP into three unobserved monthly values by the geometric mean.
- The model is cast in State Space Form and, under Gaussian distribution of the errors, the unknown parameters can be estimated by maximum likelihood, using the prediction error decomposition, performed by the Kalman filter.
- Filter and Smoother are based on the Univariate statistical treatment of multivariate models by Koopman and Durbin (2000): very flexible and convenient device for handling missing values in multivariate models and reduce the time of convergence.
- The multivariate vectors $\mathbf{y}_t^\dagger$, $t = 1, \ldots, n$, where some elements can be missing, are stacked one on top of the other to yield a univariate time series $\{y_{t,i}^\dagger, i = 1, \ldots, N, t = 1, \ldots, n\}$, whose elements are processed sequentially.

Main Results for US

- ✓ Monthly GDP presents heteroskedasticy and volatility clustering, with higher degree of clustering and a clear cut in the fluctuations prior and posterior to the great moderation in the mid 80s.
- ✓ The determinants of volatility in the US economy differ to the determinants of the level of growth: the most important determinant for the volatility is employment, followed by income. And industrial production becomes the less important.
- ✓ Confidence bands for GDP nowcast and forecast are misspecified in the constant variance model. The flexibility of our time varying model allows confidence bands to shrink and expand with the degree of uncertainty in the economy.

Table: GARCH with two regimes

	Employment	Industrial Production	Sales	Income	GDP	CI
			Measurement Equation			
$\theta_{0,i}$	0.090**	0.317**	0.096**	0.048*	0.094**	
$\theta_{1,i}$		0.676**				
β_k	-1.852 **					
			Idiosyncratic conditional means parameters			
δ_i	0.165**	0.018**	0.201**	0.685**	0.242**	
d_i	-0.157	0.915**	0.132	-0.221		
			Idiosyncratic variances parameters			
$\sigma_{\eta_i^*}$	0.140**	0.161**	0.449**	0.707**	0.607**	
			Coincident Indicator mean parameter			
ϕ						0.900**
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ϖ_1						0.092**
ϖ_2						0.001**
α_0						0.770**
α_1						0.081**
ω_i	0.369**	0.002**	0.289**	0.328**	0.012**	

Maximum likelihood estimates. CI stands for coincident indicator. The superscript "**" means that parameters are significant at 5% level, while "*" refers to 10% level. The parameters ($\vartheta_{0,i}, \vartheta_{1,i}, \delta_i, \sigma_{\eta_i^*}$) are multiply by 100 for better legibility.

Reminder: VOLINX $\sigma_t^2 = \varpi_1 I_{[1]} + \varpi_2 I_{[2]} + \alpha_0 \sigma_{t-1}^2 + \alpha_1 \sum_{i=1}^N \omega_{it} v_{it}^2$

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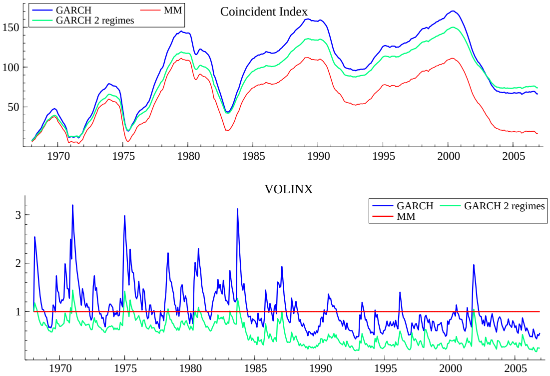
Benchmark with competitors models

Figure: The Mariano & Murasawa model with constant variance, the GARCH and the Garch with 2 regimes



We also estimate a model with 2 regimes unconditional variance without Garch part as in Stock&Watson(2002): the parameters are not significant, while they do are in the Garch formalization.

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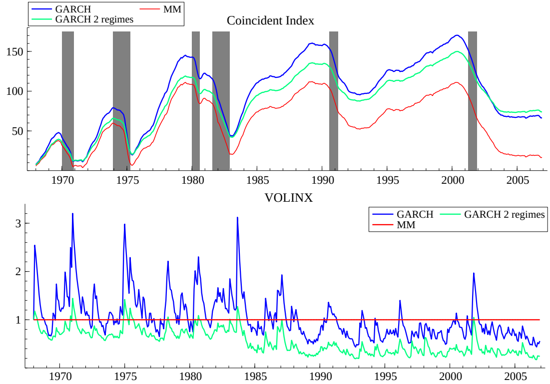

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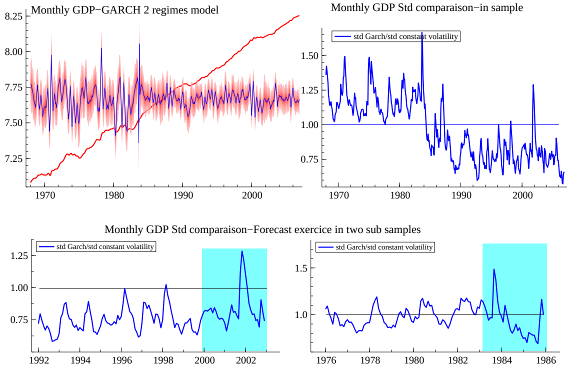
Additional checks on the model and results

- ✓ Univariate GARCH models for the single series are significant.
- ✓ The Demos-Sentana test for conditional heteroschedasticity on the residual of the constant variance model. There is evidence of heteroschedasticity.
- ✓ Test Garch model against constant variance: the two models are nested and the LR test is significant (α_0 and α_1 are sign. different from zero).Open issue: test the 2 regimes model.
- ✓ The idea of employment as relevant series for volatility is coherent with the literature of the effect macro announcement in the volatility of financial markets. It has been shown (Balduzzi, Elton and Green, 2001, Hautsch and Hess, 2002, and Andersen, Bollerslev, Diebold and Vega, 2003, among others) that one of the most important macroeconomic indicators to explain financial assets's volatility is employment.
- ✓ As as robustness check, I estimate the same model (1985M1:2005M12) substituting the innovations by the surprise of the survey data on analyst forecasts, provided by Standard and Poors Global Markets and its successor Informa Global Markets. The surprise is defined as the difference between initial announcements (change in percentage points with respect to the previous months) of the indicators and the median of analysts' forecasts. Results show that employment and income are still the most important determinants of the uncertainty, followed closely by sales and relegating industrial production to the least important.

Practical applications: VOLINX

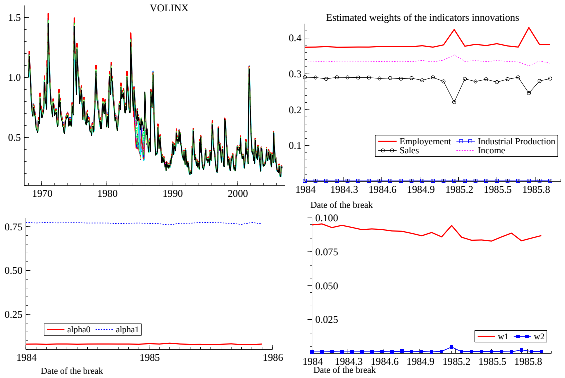


VOLINX: Surveillance of the uncertainty: VOLINX shows that, since late 60s, the US economy has suffered regular periods of stress. These have been particularly important prior to the great moderation.

Monthly GDP: Intraquarterly nowcast and forecast: The estimates of the Monthly GDP are useful for short term nowcast and forecast

Nowcasting and forecasting with correct confidence bands: the standard model that assumes constant variance later is clearly misspecified as it underestimates the fluctuations prior to the great moderation and exacerbates them posterior to mid 80s.

Dating the change regime



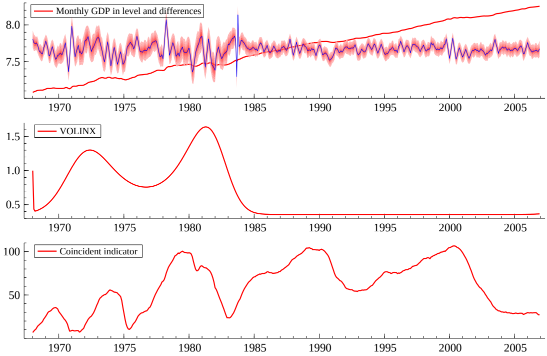
In our model the breaking date for the great moderation is exogenous. Based on Stock & Watson (2002) and Giannone & Reichlin(2008) the break date is fixed to January 1984.

the robustness of the results is checked estimating the model for a grid of breaking dates from January 1984 to December 1985.

The bottom line of this robustness check is that the degree of uncertainty over the 37 years is robust to the choice of the breaking date.

New results

Figure: GARCH model with a 3th order Fourier function



$$\sigma_t^2 = (1-\alpha_0-\alpha_1-c)+\alpha_0\sigma_{t-1}^2+\alpha_1\sum_{i=1}^{N-1}\varphi_i v_{it}^2 + c*\exp\{b_0+\sum_{j=1}^{3}[b_j^s \sin(\frac{2\pi ij}{T})+b_j^c \cos(\frac{2\pi ij}{T})]\},$$

Table: GARCH model with Fourier function

	Employment	Industrial Production	Sales	Income	GDP	CI
			State Equation			
$100 \times \theta_{0,i}$	0.097**	0.358**	0.0856**	0.050*	0.110**	
$100 \times \theta_{1,i}$		0.570**				
$100 \times \beta_k$	-1.819 **					
			Idiosyncratic conditional means			
$100 \times \delta_i$	0.179**	0.018**	0.195**	0.742**	0.247**	
d_i	-0.185	0.919**	0.208	-0.201		
			Idiosyncratic variances			
$100 \times \sigma_{\eta_i^*}$	0.104**	0.126**	0.325**	0.521**	0.460**	
			Coincident Indicator mean			
ϕ						0.890**
			Coincident Indicator variance			
α_0						0.06**
α_1						4.6 e-007
φ_i	0.505**	0.008	0.361**	0.126**		

$$\sigma_t^2 = (1-\alpha_0-\alpha_1)+\alpha_0\sigma_{t-1}^2+\alpha_1\sum_{i=1}^{N-1}\varphi_i v_{it}^2+\exp\{b_0+\sum_{j=1}^{3}[b_j^s \sin(\frac{2\pi ij}{T})+b_j^c \cos(\frac{2\pi ij}{T})]\},$$

$c = 0.604^{**}$ $b_0 = -6.234^{**}$
$b_1^s = 7.623^{**}$ $b_2^s = -2.240^{**}$ $b_3^s = 1.844^{**}$
$b_1^c = 2.570^{**}$ $b_2^c = 0.029$ $b_3^c = -0.442$

Summary

- Given a set of monthly indicators we estimate a monthly coincident index for the level and the volatility of the US economy.
- We rely on a new type of GARCH model where we replace the past square error by a linear combination of the past standardized forecasting errors of the economic indicators. The weights of the linear combination permit us to infer which are the most relevant indicators that explain the volatility of the economy.
- We estimate the monthly GDP by disaggregation of the quarterly value according to the technique for state space models developed by Harvey (1989) and Proietti(2006).

Summary (cont.)

- Our results show that the US economy suffered regular episodes of stress prior to the great moderation (stagflation, first and second oil crisis). Only two peaks of uncertainty appears after the great moderation. The first is from mid 1986 to mid 1987 (tax reform act of 1986) and the second is September 11.
- We also find that, consistently with the literature, industrial production is the most important determinant for the level of the US economy. However, the most important determinants of the volatility are employment and income, relegating industrial production to less important.
- Monthly GDP growth presents heteroscedasticity and volatility clustering with a clear cut in the fluctuations prior and posterior to the great moderation in the mid 80s. The in and out of sample forecasts of GDP have confidence intervals that shrink and expand with the degree of uncertainty in the economy. This is a useful tool for economic policy decision makers, which may adapt their decisions depending on how wide are the confidence intervals.

Future agenda

- ✓ Include more indicators in the analysis. As mentioned in the introduction, we constrain ourselves to the same set of indicators as in S&W.
- ✓ In the Smoother and filter make use of a more precise approximation of the non linear constraint caused by log transformation, e.g. sequential post mode on a Taylor expansion as in Proietti(2006).
- ✓ Estimating endogenously the breaking date of the great moderation. This means to use of switching regimes GARCH models with regimes treated endogenously. The literature exist for traditional volatility settings (i.e. observed components) but its adaptation to state space models deserves further research.
- ✓ One first possibility is considering a transition mechanism, i.e. logistic function, instead of a break in the level, with a location parameter (as in Amado & Teräsvirta 2008).

Surveillance on the economy