Global Macroeconomic Uncertainty

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Goal of the paper

1. Measure global macroeconomic uncertainty
2. Has global macroeconomic uncertainty an impact on country specific macroeconomic performance?

Motivation

- *Great Recession* had its origins in the US but spread quickly around the world
- its quick expansion is not well understood
  - ⇒ Rose & Spiegel (2010) and Kamin & DeMarco (2012): No evidence that countries with larger cross-border financial linkages to the United States were more affected in terms of either equity prices or business cycles
- rekindled interest in international shock transmission channels

Motivation

- direct contagion: direct real and financial linkages (trade relationships, major bankruptcy in one country causes large losses for investors in other countries)
  $\Rightarrow$ first moments correlation

- indirect contagion: residual category (reduced confidence of investors, concerns about credit and liquidity risk, or more generally, *uncertainty*)
  $\Rightarrow$ impact of second moments

- growing literature investigating the role of indirect contagion

⇒ Bacchetta et al. (AER 2012) concept of **risk panics**

- A weak fundamental (e.g. the health of financial institutions in the US, the scale of debt in Greece) suddenly becomes a focal point of fear everywhere.
- This fundamental then takes on the role of a coordination device for a self-fulfilling shift in risk perceptions, even without any dramatic or sudden change in the fundamental itself.

⇒ Bacchetta & van Wincoop (JIE 2013)

- Spikes in implied volatility measures during the recent crisis occurred simultaneously across the globe, and were not associated with the transmission of shocks through financial markets.

⇒ There are several **theoretical arguments** relating uncertainty to a slowdown in economic activity, as it:

- hampers optimal resource allocation by
  - distorting the price mechanism (Friedman, JPE 1977)
  - inducing precautionary saving (Gosh & Ostry, JME 1997)
  - shortening contract duration (Rich & Tracy, REStat 2004)
- induces firms to delay their decisions on investment and hiring (Bernanke, QJE 1983, Bloom, Econometrica 2009)
- pushes up the cost of finance
  (Gilchrist et al., 2010, Pastor & Veronesi, J Finance forthcoming)

- Empirical research has focused on estimating macroeconomic uncertainty and its potential impact on macroeconomic performance on a **national level**

- To test for the relationship between macroeconomic uncertainty and performance a Garch-in-mean model can be used

$$x_t = \Phi_0 + \sum_{k=1}^{p} \Phi_k x_{it-k} + \delta H_t + \eta_t, \qquad \eta_{it} \sim N(0, H_t)$$

typically x_t includes output growth and inflation

- Uncertainty is measured by the variance of the stochastic, or unpredictable, component

⇒ *Grier et al. (2004, JAE), Bredin and Fountas (2009, JIMF), Fountas et al (2006 OBES), Fountas and Karanasos (2007, JIMF) ...*

- these paper test whether real and/or nominal uncertainty affects the (conditional) mean of real and nominal variables
- a general result is that uncertainty plays a role explaining the performance of macroeconomic variables

⇒ Parallel empirical literature on the comovement of macroeconomic variables using dynamic factor models

- on international business cycle (Kose et al. 2003, AER, JIE 2008, Crucini et al., RED 2011)
- on global inflation (Ciccarelli and Mojon 2010, REStat, Mumtaz and Surico, JEEA 2012)

- Comovement is defined as common shocks to the mean. No attempt has made to analyze the impact of common or global macroeconomic uncertainty, i.e. changes in the second moments of common shocks

Our approach

Combination of two strands of literature

- **Dynamic factor models:** Set up of a DFM, that decomposes inflation and output growth into a common and country-specific components

- **Uncertainty literature (GARCH-in-Mean methods):** The conditional variances of all factors are modeled as GARCH processes and interpreted as reflecting uncertainty in the underlying factor

We estimate a measure for global macroeconomic uncertainty and analyze its impact on individual countries' macroeconomic performance

A Dynamic Factor Model

- Starting point is a bivariate DFM:

$$\begin{bmatrix} y_{it} \\ \pi_{it} \end{bmatrix} = \begin{pmatrix} \Gamma_i^y & 0 \\ 0 & \Gamma_i^\pi \end{pmatrix} \begin{bmatrix} R_t^y \\ R_t^\pi \end{bmatrix} + \begin{bmatrix} I_{it}^y \\ I_{it}^\pi \end{bmatrix}$$

- The common factors in inflation and output growth are modeled as $AR(p)$ processes:

$$R_t^y = \sum_{k=1}^{p} \rho_k R_{t-k}^y + \varepsilon_t^y, \qquad \varepsilon_t^y \sim N\left(0, \sigma_t^y\right)$$

$$R_t^\pi = \sum_{k=1}^{p} \theta_k R_{t-k}^\pi + \varepsilon_t^\pi, \qquad \varepsilon_t^\pi \sim N\left(0, \sigma_t^\pi\right)$$

- The idiosyncratic factors are modeled as bivariate $VAR(p)$ processes:

$$x_{it} = \sum_{k=1}^{p} \Phi_k^i x_{it-k} + \eta_{it}, \qquad \eta_{it} \sim N(0, H_{it})$$

where

$$x_{it} = \begin{bmatrix} I_{it}^{y} \\ I_{it}^{\pi} \end{bmatrix}, \ \Phi_k^i = \begin{bmatrix} \phi_{k11}^i & \phi_{k12}^i \\ \phi_{k21}^i & \phi_{k22}^i \end{bmatrix}, \ \eta_t = \begin{bmatrix} \eta_{it}^{y} \\ \eta_{it}^{\pi} \end{bmatrix}, \ H_{it} = \begin{bmatrix} h_{it}^{y} & h_{it}^{y\pi} \\ h_{it}^{y\pi} & h_{it}^{\pi} \end{bmatrix}$$

- The orthogonality of common factors allows for (time-varying) variance decomposition into common vs idiosyncratic factors.
- Real and nominal variables can be correlated at the same geographical level.

Modeling Uncertainty

Global real uncertainty: $\sigma_t^y = \alpha_0^y + \alpha_1^y \varepsilon_{t-1}^{y2} + \alpha_2^y \sigma_{t-1}^y$

Global nominal uncertainty: $\sigma_t^\pi = \alpha_0^\pi + \alpha_1^\pi \varepsilon_{t-1}^{\pi 2} + \alpha_2^\pi \sigma_{t-1}^\pi$

Country specific uncertainties CCC-$GARCH(1,1)$:

$$h_{it}^y = \beta_{i0}^y + \beta_{i1}^y \eta_{it-1}^{y2} + \beta_{i2}^y h_{it-1}^y$$
$$h_{it}^\pi = \beta_{i0}^\pi + \beta_{i1}^\pi \eta_{it-1}^{\pi 2} + \beta_2^i h_{it-1}^\pi$$
$$h_{it}^{y\pi} = \rho_i \sqrt{h_{it}^y h_{it}^\pi}$$

A Dynamic Factor Garch-in-Mean Model

- The factor model is augmented by including measures of global real and nominal uncertainty:

$$\begin{bmatrix} y_{it} \\ \pi_{it} \end{bmatrix} = \begin{pmatrix} \Gamma_i^y & 0 \\ 0 & \Gamma_i^\pi \end{pmatrix} \begin{bmatrix} R_t^y \\ R_t^\pi \end{bmatrix} + \begin{pmatrix} \delta_{11}^i & \delta_{12}^i \\ \delta_{21}^i & \delta_{22}^i \end{pmatrix} \begin{bmatrix} \sigma_t^y \\ \sigma_t^\pi \end{bmatrix} + \begin{bmatrix} I_{it}^y \\ I_{it}^\pi \end{bmatrix}$$

- δ^i capture the sensitivity of output growth and inflation in country i to global real and nominal uncertainty.

Data

- **Sample (N=9 countries)**
  (reflect about 80% of OECD GDP)

- Canada, United States, France, Germany, Italy, Spain, Netherlands, United Kingdom, Japan

- **Data**
  (OECD Main Economic Indicators, seasonally adjusted)
  - covers the period from 1965 M1-2012 M05
  - **Inflation**: annualized monthly difference of log CPI
  - **Output**: annualized monthly difference of log Industrial Production

Estimation

- The model consists of 273 parameters, $2+(2 \times N)$ latent factors and time varying conditional variances on all latent factors.
- In order to derive the likelihood function of the model we put the model in state space form (not standard due to GARCH errors) and use the Kalman filter. Details LL function
- We employ a Metropolis-Hastings (MH) algorithm. MH algorithm are widely used in applied econometrics, particularly for the estimation of GARCH models. Details MH algorithm

Results

Global real factor and uncertainty

$$R_t^y = -0.247R_{t-1}^y + 0.011R_{t-2}^y + 0.168R_{t-3}^y + 0.053R_{t-4}^y + \varepsilon_t^y$$
$$\sigma_t^y = 0.454 + 0.428\varepsilon_{t-1}^{y2} + 0.118\sigma_{t-1}^y$$

Global nominal factor and uncertainty

$$R_t^\pi = 0.548R_{t-1}^\pi + 0.067R_{t-2}^\pi + 0.215R_{t-3}^\pi + 0.124R_{t-4}^\pi + \varepsilon_t^\pi$$
$$\sigma_t^\pi = 0.004 + 0.188\varepsilon_{t-1}^{\pi 2} + 0.808\sigma_{t-1}^\pi$$

Figure: Global factors

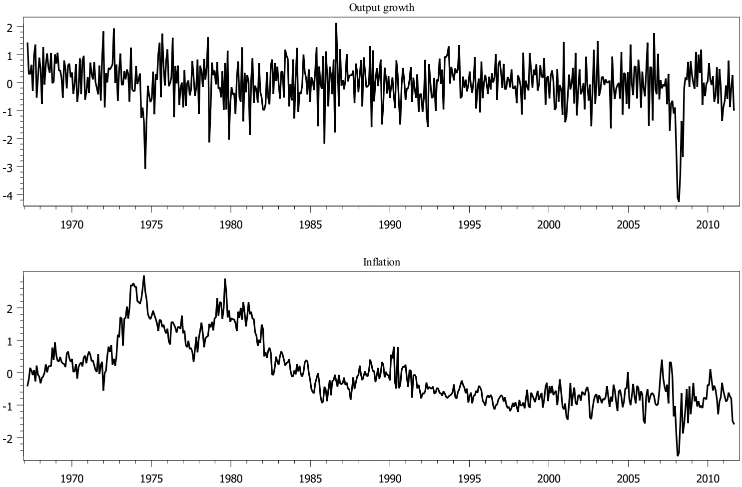

Figure: Global real and nominal uncertainty

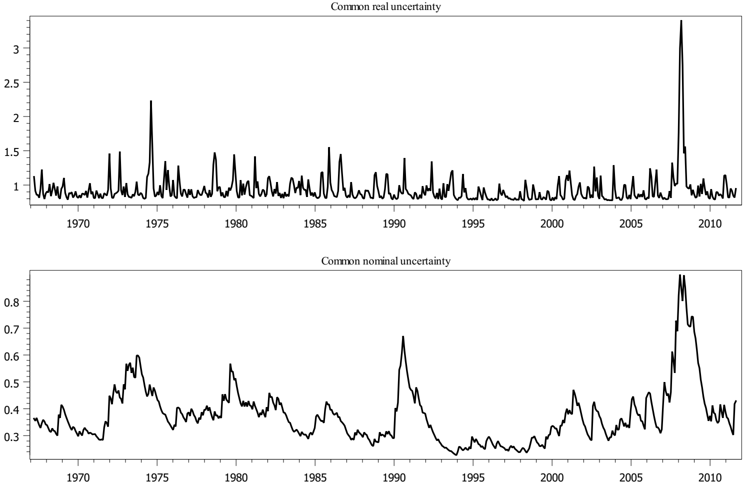

Table: Garch-in-mean effects

	Real Uncertainty on		Nominal Uncertainty on	
	Output Growth δ^i_{11}	Inflation δ^i_{12}	Output Growth δ^i_{21}	Inflation δ^i_{22}
Canada	**-1.46** [-2.01, -0.92]	0.05 [-0.11, 0.22]	-0.48 [-2.86, 1.92]	0.59 [-0.41, 1.58]
France	0.01 [-0.48, 0.49]	**-0.29** [-0.42, -0.16]	1.03 [-0.91, 2.95]	**1.99** [0.97, 2.98]
Germany	-0.45 [-1.08, 0.16]	0.03 [-0.07, 0.13]	0.05 [-2.04, 2.20]	-0.23 [-1.04, 0.59]
Italy	**-1.74** [-2.27, -1.24]	-0.20 [-0.28, 0.11]	**7.44** [5.68, 9.22]	**2.11** [0.83, 3.32]
Japan	**-1.06** [-1.83, -0.30]	-0.15 [-0.33, 0.03]	**4.45** [1.74, 7.07]	**-1.37** [-2.43, -0.31]
Netherlands	**1.49** [0.88, 2.13]	**0.27** [0.07, 0.48]	**-4.14** [-6.12, -2.20]	**-1.59** [-2.72, -0.44]
Spain	**-0.74** [-1.21, -0.27]	**0.17** [0.03, 0.30]	**2.23** [0.27, 4.11]	**-2.85** [-3.57, -2.14]
UK	0.06 [-0.30, 0.41]	**0.15** [0.03, 0.26]	**-2.75** [-4.37, -1.16]	**-1.39** [-2.03, -0.75]
US	-0.21 [-0.71, 0.30]	-0.24 [-0.41, 0.09]	0.64 [-1.36, 2.64]	0.41 [-0.88, 1.71]

- Global real uncertainty has a negative effect for output growth in four countries and increases inflation in the Netherlands, Spain and the UK.
- Global nominal uncertainty influences the performance of inflation rates and output growth with mixed signs.
- With the exception of Germany global uncertainty has an effect in all countries considered.

Summary

- We use a DFM model to decompose output growth and inflation into common and country-specific factors and interpret their corresponding conditional variances as global and country-specific uncertainty.
- The uncertainty measures are included as explanatory variables in the mean equations.
- In a sample of OECD countries, we find the Great Moderation starting in the mid-1980s to be associated with a discernible slowdown of both global and national measures of uncertainty.
- The Great Recession is reflected in a dramatic increase in both nominal and real global uncertainty, while not affecting national uncertainties.
- Global macroeconomic uncertainty effects inflation and/or output growth in all countries except Germany.

Thank you for your attention!

Deriving the Likelihood function

$\Rightarrow$ put model in state-space form

$$\xi_t = Z\alpha_t + Ax_t$$
$$\alpha_{t+1} = T\alpha_t + \eta_t, \quad \eta_t \sim N(0, Q_t)$$

- $\xi_t = \begin{bmatrix} y_{1t} & \pi_{1t} & y_{2t} & \pi_{2t} & \dots & y_{Nt} & \pi_{Nt} \end{bmatrix}'$ (dimension of ξ_t is 18×1)
- shocks in the state vector is necessary due to *GARCH* variances and follows Harvey et al. (1992 JoE)
- $\alpha_t = [R_t^y \; R_t^\pi \quad I_{1t}^y \; I_{1t}^\pi \; \dots \; I_{Nt}^y \; I_{Nt}^\pi \quad \varepsilon_t^y \; \varepsilon_t^\pi \quad \eta_{1t}^y \; \eta_{1t}^\pi \; \dots \; \eta_{Nt}^y \; \eta_{Nt}^\pi]' + 3$ lags of all AR states (dimension of α_t is 100×1)
- x_t is a vector of exogenous variables; here it contains the *GARCH* series of the common factors, i.e. global real and nominal uncertainty

Deriving the Likelihood function

First Step: Prediction

1. expectation of state vector: $\alpha_{t|t-1} = E[\alpha_t|\Xi_{t-1}] = T\alpha_{t-1|t-1}$
2. cov: $P_{t|t-1} = E[(\alpha_t - \alpha_{t|t-1})(\alpha_t - \alpha_{t|t-1})'] = TP_{t-1|t-1}T' + Q_t$
3. prediction error: $v_{t|t-1} = \xi_t - \xi_{t|t-1} = \xi_t - Z\alpha_{t|t-1}$
4. conditional variance of v_t: $F_{t|t-1} = ZP_{t|t-1}Z'$

Second Step: Updating (use prediction error to calculate $\alpha_{t|t}$)

5. $\alpha_{t|t} = \alpha_{t|t-1} + K_t v_{t|t-1}$ $K_t = P_{t|t-1}Z'F^{-1}_{t|t-1}$ is the *Kalman gain*
6. $P_{t|t} = P_{t|t-1} - K_t \Gamma P_{t|t-1}$

log-likelihood : $l(\theta) = -\frac{1}{2}\sum \ln((2\pi)|F_{t|t-1}|) - \frac{1}{2}\sum v'_{t|t-1}F^{-1}_{t|t-1}v_{t|t-1}$

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- we us a **component wise Metropolis-Hastings** algorithm
  - ⇒ draw from a proposal density and use an acceptance rule
  - ⇒ if a draw does not get accepted the previous draw is kept
- to deal with the low efficiency problem of the MH algorithm in large dimension we use the component wise MH algorithm
- let $\Theta = (\Theta_1, \ldots, \Theta_d)$ be a Markov chain of order d
- divide the elements of Θ into z components, denoted by Θ_j
- let $\theta_{n1}, \ldots, \theta_{nz}$ be the state of the components $\Theta_1, \ldots, \Theta_z$ at time n

⇒ for each $j = 1, \ldots, z$ use the following algorithm

1. Simulate a candidate ζ_{nj} from proposal density ψ

2. Compute the acceptance probability γ according to

$$\gamma = \min\left\{\frac{p\left(\zeta_{nj} \mid \theta'_{n-j}\right)}{p\left(\theta_{nj} \mid \theta'_{n-j}\right)}, 1\right\}$$

   where $p(\cdot)$ denotes the posterior density. Thus, $p\left(\theta_{nj} \mid \theta'_{n-j}\right)$ is the full conditional posterior distribution for the components Θ_{nj} given the current state θ'_{n-j} of all other components

3. Set $\Theta_{n+1j} = \zeta_{nj}$ if the candidate is accepted, otherwise set $\Theta_{n+1j} = \Theta_{nj}$.

Proposal density

1. use first principal component of IP growth and inflation across countries as proxies for the common factors
2. ML estimation of AR(4) Garch (1,1) models of each principal component
3. ML estimation of VMAX(4) CCC-Garch (1,1) models for each country

$\Rightarrow$ note that the principal components are only used for getting the parameters of the proposal density

Proposal density

Parameters common factors

$$y_t^{PC} = \sum_{k=1}^{p} \rho_k y_{t-k}^{PC} + \varepsilon_t^y, \qquad \sigma_t^y = \alpha_0^y + \alpha_1^y \varepsilon_{t-1}^{y2} + \alpha_2^y \sigma_{t-1}^y$$

$$\pi_t^{PC} = \sum_{k=1}^{p} \theta_k \pi_{t-k}^{PC} + \varepsilon_t^\pi, \qquad \sigma_t^\pi = \alpha_0^\pi + \alpha_1^\pi \varepsilon_{t-1}^{\pi 2} + \alpha_2^\pi \sigma_{t-1}^\pi$$

Proposal density

Parameters country factors

⇒ given the common factors, the model can be estimated separately for each country

$$\begin{bmatrix} Y_{it} \\ \pi_{it} \end{bmatrix} = \begin{pmatrix} \Gamma_i^y & 0 \\ 0 & \Gamma_i^\pi \end{pmatrix} \begin{bmatrix} y_t^{PC} \\ \pi_t^{PC} \end{bmatrix} + \begin{pmatrix} \delta_{11}^i & \delta_{12}^i \\ \delta_{21}^i & \delta_{22}^i \end{pmatrix} \begin{bmatrix} \sigma_t^y \\ \sigma_t^\pi \end{bmatrix} + \begin{bmatrix} I_{it}^y \\ I_{it}^\pi \end{bmatrix}$$

⇒ $\left[I_{it}^y, I_{it}^\pi\right]'$ is a $VAR(p)$ with the conditional var-cov modeled as CCC-Garch(1,1)

⇒ solve that model such that residuals are not autocorrelated and apply ML

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