Credit Conditions and the Effects of Economic Shocks: Amplification and Asymmetries

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2. Do they amplify the effects of structural economic shocks?
3. Do they generate asymmetries in the effects of shocks depending on the size/sign of the shock?

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  1. large negative shocks have larger effects during low growth regimes (Weise, 1999).

Why large VARs for structural analysis?

- One can compute informative responses (confidence bands are not too wide) to shocks in a large Bayesian VAR if shrinkage prior hyperparameters are estimated (Banbura, Giannone and Reichlin, 2010; Giannone, Lenza and Primiceri, 2015).

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- One can employ a VAR with many different measures of economic activity and credit conditions (Gilchrist, Yankov and Zakrajsek, 2009).

Credit Conditions and the Macroeconomy

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- Because the empirical results above are based on linear models, there is no role for credit to act as a nonlinear propagator of shocks as in Balke (2000) and suggested by some DSGE models.
- An exception based on the sign/size of *credit market shocks* using a projection approach is Barnichon, Matthes and Ziegenbein (2017).

Main Features of our Modelling Approach

- Dimensionality issues are sorted by using the Bayesian MAI approach as in Carriero, Kapetanios and Marcellino (2016a), and the use of the triangularization in Carriero, Clark and Marcellino (2016b).
- A small set of factors and common structural shocks drive the dynamics of the large set of variables.
- All elements of the variance-covariance matrix are allowed to change over regimes including the covariances (in contrast with the approach in Carriero, Clark and Marcellino (2016b)).
- The Bayesian estimation of all parameters in the smooth transition function relies on Lopes and Salazar (2005) and Galvao and Owyang (2017).

The MAI model

- Start with a VAR for the $N \times 1$ Y_t vector:

$$Y_t = \sum_{u=1}^{p} C_u Y_{t-u} + \varepsilon_t; \varepsilon_t \sim N(0, \Sigma).$$

- The MAI reduces the number of coefficients to estimate by assuming that Y_t is predicted by a small set of indices (Reinsel, 1983):

$$Y_t = \sum_{u=1}^{p} A_u B_0 Y_{t-u} + \varepsilon_t,$$

or

$$Y_t = \sum_{u=1}^{p} A_u F_{t-u} + \varepsilon_t,$$

where

$$F_t = B_0 Y_t$$

and B_0 is $R \times N$ where R is the number of indices/factors with one entry at each row of B_0 normalized to 1.

- Allow for regime changes as:

$$Y_t = \sum_{u=1}^{p} A_u F_{t-u} + \sum_{u=1}^{p} \Pi_t(\gamma, c, x_{t-1}) D_u F_{t-u} + \varepsilon_t,$$

where the transition function is

$$\Pi_t(\gamma, c, x_{t-1}) = \frac{1}{1 + \exp(-(\gamma/\sigma_x)(x_{t-1} - c))},$$

and one of the factors ($r = 1, ..., R$) is employed as transition variable:

$$x_t = g_t^{(r)} = \frac{1}{12} \sum_{j=0}^{11} b_0^{(r)} Y_{t-j},$$

where we use Y on Y growth (monthly data) to get regimes of enough duration.

The ST-MAI model II

- Let the variance-covariance matrix to change over the regime as:

$$\begin{aligned} var(\varepsilon_t) &= \Sigma_t \\ \Sigma_t &= (1 - \Pi_t(\gamma, c, x_{t-1}))\Sigma_1 + \Pi_t(\gamma, c, x_{t-1})\Sigma_2. \end{aligned}$$

- Only few additional parameters are required to capture variance changes over time based on a time-varying weighted average. Regime-switching covariances may have a key role on the impulse response analysis.

Estimation I

- Gibbs sampling over four steps/blocks.

1. Conditional on previous draws of $\Sigma_1^{(s-1)}, \Sigma_2^{(s-1)}, A^{(s-1)}$ and $B_0^{(s-1)}$, a joint draw $\gamma^{(s)}, c^{(s)}$ is obtained using a Metropolis step (Lopes and Salazar, 2005; Galvao and Owyang, 2017). The smoothing parameter has a gamma prior and proposal. The threshold has a normal prior and proposal. Both proposals have hyperparameters set to achieve around 30% acceptance rates. Candidate threshold values are constrained so 15% of observations are in each regime.

Estimation II

2. Conditional on $\gamma^{(s)}, c^{(s)}, A^{(s-1)}$ and $B_0^{(s-1)}$, $\Sigma_1^{(s)}$ and $\Sigma_2^{(s)}$ are drawn using inverse-Wishart proposal and priors in a Metropolis step (Galvao and Owyang, 2017). The proposal distribution is $\Sigma_1^{-1} \sim W(C_1^{-1}, pv_1)$ with $pv_1 = pv_0 + \Delta_1 \sum_{t=1}^{T} I(x_{t-1}^{(s)} \leq c)$ and $C_1 = \Delta_{\Sigma_1} \left[\sum_{t=1}^{T} e_{1t} e'_{1t} \right]$ where $e_{1t} = (1 - \Pi_t(\gamma^{(s)}, c^{(s)}, x_{t-1}^{(i,s-1)})\varepsilon_t^{(s-1)}$. There is a similar proposal for Σ_2^{-1}. Hyperparameters Δ_{Σ_1} and Δ_{Σ_2} are set to achieve 30% acceptance rates.
3. Conditional on $\Sigma_1^{(s)}, \Sigma_2^{(s)}, \gamma^{(s)}, c^{(s)}$ and $B_0^{(s-1)}$, $A^{(s)}$ is drawn using the triangularization proposed by Carriero et al (2016b). We use a modification of the Minnesota Normal prior. Set $\lambda_1 = 1$ and $\lambda_2 = 0.5$ (select using likelihood).

Estimation III

4. Conditional on $\Sigma_1^{(s)}, \Sigma_2^{(s)}, A^{(s)}$ and $\gamma^{(s)}, c^{(s)}$, $B_0^{(s)}$ is drawn using a random-walk-metropolis step as in Carriero et al (2016a). Hyperparameter Δ_b is calibrated to achieve rejection rates of around 70%.

Computing Responses to Shocks I

- If we multiply the STMH-MAI by B_0, we get:

$$F_t = B_0 \sum_{u=1}^{p} A_u F_{t-u} + B_0 \sum_{u=1}^{p} \Pi_t(\gamma, c, x_{t-1}) D_u F_{t-u} + u_t,$$

with

$$u_t = B_0 \varepsilon_t, \quad var(u_t) = \Omega_t = B_0 \Sigma_t B_0'.$$

- A small set of common shocks drives the dynamics of the system.

Computing Responses to Shocks II

- The effect of the r^{th} common shock on Y at the impact in regime 1 is (as in Carriero et al, 2016):

$$v_1^{(r)} = \Sigma_1 B_0' P_{1,(r)}^{-1\prime}$$

where $P_{1,(r)}^{-1\prime}$ refers to the column of shock r in the matrix $P_1^{-1\prime}$ $(r = 1, ..., R)$ obtained via Cholesky decomposition as $\Omega_1 = B_0 \Sigma_1 B_0' = P_1 P_1'$. Equivalently, for regime 2 at impact:

$$v_2^{(r)} = \Sigma_2 B_0' P_{2,(r)}^{-1\prime}.$$

Computing Responses to Shocks III

- The responses of Y to $v^{(r)}$ at horizon h conditional on the history at t are:

$$\begin{aligned} GR_{h,r,t} &= E[Y_{t+h}|I_t, v^{(r)}; \Sigma_{t+h}|I_t, v^{(r)}; A, B_0, \gamma, c] \\ &\quad - E[Y_{t+h}|I_t; \Sigma_{t+h}|I_t; A, B_0, \gamma, c], \end{aligned}$$

  where $I_t = (Y'_t, .., Y'_{t-p+1})'$ and $A = (A_1 ... A_p, D_1 ... D_p)'$.

- We use draws as

$$\begin{aligned} \varepsilon^{(k)}_{t+h} &\sim N(0, \Sigma^{(k)}_{t+h}) \\ \Sigma^{(k)}_{t+h} &= (1 - \Pi_{t+h}(\gamma, c, x^{(k)}_{t+h-1}))\Sigma_1 + \Pi_{t+h}(\gamma, c, x^{(k)}_{t+h-1})\Sigma_2. \end{aligned}$$

  where $k = 1, ..., K$, to compute both conditional expectations.

Computing Responses to Shocks IV

- In practice, we split the time periods between two regimes ($\Pi_t(\gamma, c, x_{t-1}) \geq 0.5$ is the upper regime) to compute regime-dependent responses while allowing for regime-switching after the shock:

$$
\begin{aligned}
GR_{h,r}^{reg1} &= 1/T_1 \sum_{t=1}^{T_1} GR_{h,r,t}^{(reg1)}(v_1^{(r)}) \\
GR_{h,r}^{reg2} &= 1/T_2 \sum_{t=1}^{T_2} GR_{h,r,t}^{(reg2)}(v_2^{(r)})
\end{aligned}
$$

- We also need to consider parameter uncertainty.

Computing Responses to Shocks V

- Complete algorithm to compute regime-conditional responses:

1. Draw a set of parameters – $A^{(j)}, B_0^{(j)}, \Sigma^{(j)}, \gamma^{(j)}, c^{(j)}$– from saved posterior distribution draws.
2. Using $\Pi_t(\gamma^{(j)}, c^{(j)}, x_{t-1}^{(j)})$, define the sets $I^{(reg1)}$ and $I^{(reg2)}$.
3. Using $A^{(j)}, B_0^{(j)}, \Sigma^{(j)}, \gamma^{(j)}, c^{(j)}, I^{(reg1)}$ and $v_1^{(r)}$, select $t = 1$ (a history from $I^{(reg1)}$) to compute a set of K paths for $h = 1, ..., H$ with and without the impact of $v_1^{(r)}$ by simulating the system with draws from $\varepsilon_{t+h}^{(k)} \sim N(0, \Sigma_{t+h}^{(k)})$. By averaging over the K paths, compute $GR_{h,r,t=1}^{(reg1)}$. Then repeat for $t = 2, ..., t = T_1$. Finally, compute $GR_{h,r}^{reg1}$ by averaging over saved $GR_{h,r,t}^{(reg1)}$
4. Using $A^{(j)}, B_0^{(j)}, \Sigma^{(j)}, \gamma^{(j)}, c^{(j)}, I^{(reg2)}$ and $v_2^{(r)}$, follow the algorithm in (3) using $I^{(reg2)}$ to obtain $GR_{h,r}^{reg2}$.

Computing Responses to Shocks VI

5. Repeat 1-4 for $j = 1, ..., J$.
6. Use $GR_{h,r}^{reg1,(j)}$ and $GR_{h,r}^{reg2,(j)}$ for $j = 1, .., J$ to compute the median response and 68% confidence intervals conditional on each regime for $h = 1, ..., H$.

Asymmetries from the Sign/Size of the Shock I

- We measure asymmetries due to the sign of the shock using

$$
\begin{aligned}
ASY_{h,r}^{+-(reg1)} &= 1/T_1 \sum_{t=1}^{T_1} \left[GR_{h,r,t}^{(reg1)}(v_1^{(r)}) + GR_{h,r,t}^{(reg1)}(-v_1^{(r)}) \right] \\
ASY_{h,r}^{+-(reg2)} &= 1/T_2 \sum_{t=1}^{T_2} \left[GR_{h,r,t}^{(reg2)}(v_2^{(r)}) + GR_{h,r,t}^{(reg2)}(-v_2^{(r)}) \right].
\end{aligned}
$$

We use 68% bands to assess whether either $ASY_{h,r}^{+-(reg1)}$ or $ASY_{h,r}^{+-(reg2)}$ are nonzero.

Asymmetries from the Sign/Size of the Shock II

- We measure asymmetries due to size of the shock using

$$
\begin{aligned}
ASY_{h,r}^{ls(reg1)} &= 1/T_1 \sum_{t=1}^{T_1} \left[GR_{h,r,t}^{(reg1)}(2v_1^{(r)}) - 2 * GR_{h,r,t}^{(reg1)}(v_1^{(r)}) \right] \\
ASY_{h,r}^{ls(reg2)} &= 1/T_2 \sum_{t=1}^{T_2} \left[GR_{h,r,t}^{(reg2)}(2v_2^{(r)}) - 2 * GR_{h,r,t}^{(reg2)}(v_2^{(r)}) \right].
\end{aligned}
$$

If large shocks have different effects from small shocks we expect that either $ASY_{h,r}^{ls(reg1)}$ or $ASY_{h,r}^{ls(reg2)}$ will be nonzero for a set of horizons and shocks. We again use 68% bands to asssess this.

Conclusions I

- Smooth Transition MAI models are an effective new tool to find empirical evidence of amplification effects and asymmetries in responses to shocks when considering a large set of endogenous variables.

Conclusions II

- Credit conditions drive regime-switching dynamics in a set of 20 economic and financial variables.
- During high credit stress regimes, the effect of some structural shocks are amplified; positive and negative shocks may have asymmetric effects; and large shocks may have disproportionate effects to small shocks.
- The duration of financial fragility episodes depends crucially on the type, size and sign of the shocks hitting the economy. Episodes can be shorter if large good shocks hit the economy (including loosing the monetary policy stance).

Additional Empirical Exercises I

- We change the order between *F_mp* and *F_credit* when computing responses: no major change in responses to credit and MP shocks.
- We compute responses using a small STVAR of IP, Unem, CPI, FFR (shd), EBP: activity and monetary policy shocks imply qualitatively different responses.