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

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Credit Conditions and the Macroeconomy

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- Depending on financial conditions, the effects of shocks may change because of financial amplification mechanisms (Kirshnamurthy, 2010).
- 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).
- Financial conditions as a trigger of amplification effects from economic shocks is not the same as saying that adverse financial shocks have stronger effects than favorable shocks (as in Barnichon, Matthes and Ziegenbein, 2018).

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1. Do they change the dynamic interactions of economic variables by characterizing different regimes?
2. Do they amplify the effects of structural economic shocks?
3. Does the transmission mechanism lead to different effects from small vs. large and positive vs. negative shocks?

Why Smooth Transition VARs?

- They characterise changes in the dynamic propagation of shocks by changes in regimes. They are popular to model how the transmission of shocks – monetary policy (Weise, 1999), fiscal policy (Auerback and Goridnichenko, 2012), uncertainty (Caggiano et al, 2014)– changes over business cycle regimes.

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- They are able to provide evidence of amplification effects due to credit as the evidence in Balke (2000) for the commercial paper spread. They are also useful to show how the effects of financial shocks on inflation are amplified in periods of financial stress as in Galvao and Owyang (2017).

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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- The information set available to identify a structural shock may have an impact on the responses computed (Forni, Gambetti and Sala, 2014; Caldara and Herbst, 2019).
- One can employ a VAR with many different measures of economic activity and credit conditions (Gilchrist, Yankov and Zakrajsek, 2009).

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.

The ST-MAI model I

- 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.

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%.

Variables and Factors

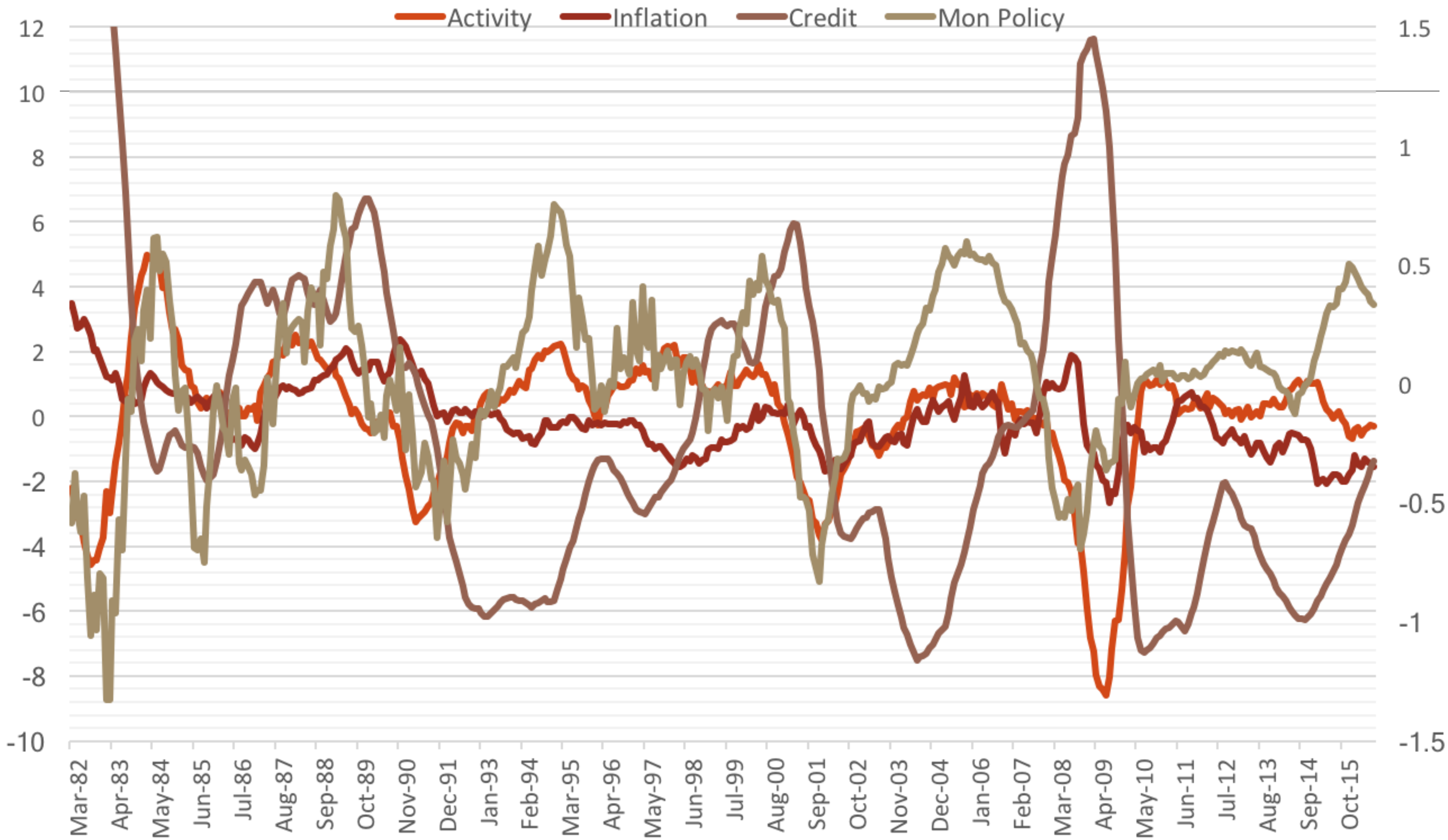
	Factor	Trans.
Employees nonfarm	activity	Log-diff
Avg hourly earnings	activity	Log-diff
Personal income	activity	Log-diff
Consumption	activity	Log-diff
Industrial Production	activity	Log-diff
Capacity utilization	activity	Log-diff
Unemp. Rate	activity	Log-diff
Housing Starts	activity	Log-diff
CPI	inflation	Log-diff
PPI	inflation	Log-diff
PCE deflator	inflation	Log-diff
PPI ex food and energy	inflation	Log-diff
FedFunds + shadow rate	Mon. Pol.	diff
1year_rate	Mon. Pol.	diff
EBP	Credit	levels
BAA spread	Credit	levels
Mortgage Spread	Credit	levels
TED Spread	Credit	levels
CommPaper Spread	Credit	levels
Term Spread (10y-3mo)	Credit	levels

Estimation period: 1982M3-2016M8 (pre-sample from 1974 for B RW priors).

Series are standardized.

N=20; p=13;

MAI model: Y on Y Factors



Note: Monetary policy factor in the right axis.

Correlation with MAI Factors

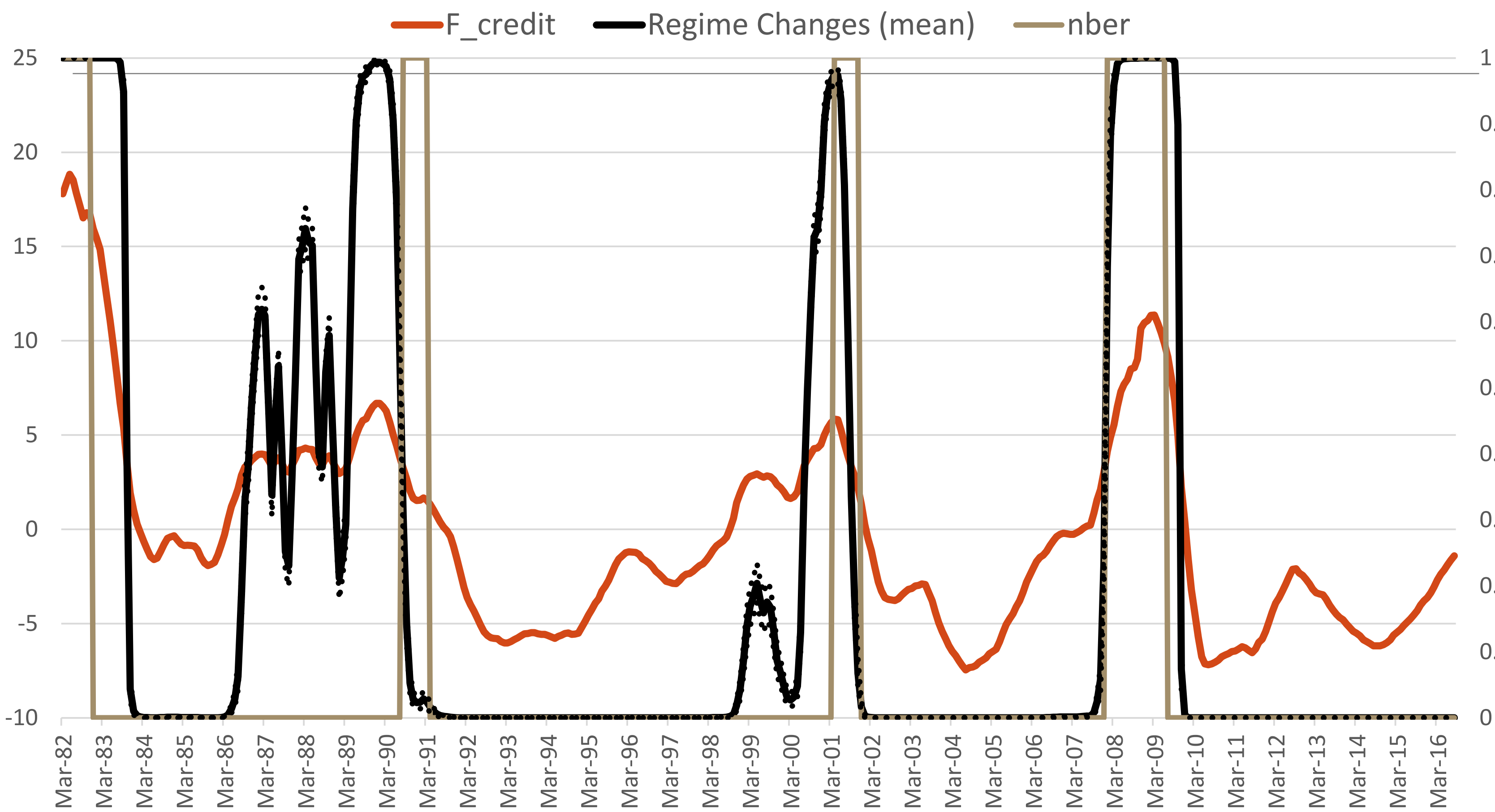
	F_infl	F_mp	F_cred	PhilFed Activity	Chicago FCI	Adjusted CFCI
F_activity	0.06	0.61	-0.47	**0.86**	-0.39	-0.02
F_inflation	1	-0.13	0.48	-0.11	0.54	0.12
F_mp	-0.13	1	-0.49	0.63	-0.34	-0.07
F_credit	0.48	-0.49	1	-0.51	**0.78**	**0.53**

Choosing ST-MAI Specification

	Average Likelihood $E_\theta(lnf(y\|\theta))$	BIC
ST-MAI with F_activity (λ_1=1;Δ_Σ=25/110; $\Delta_{\gamma,c}$=0.01)	-7820.760	28271.735
ST-MAI with F_inflation (λ_1=1;Δ_Σ=120/20; $\Delta_{\gamma,c}$=0.01)	-8004.157	28638.529
ST-MAI with F_mp (λ_1=1;Δ_Σ=20/120; $\Delta_{\gamma,c}$=0.01)	-7859.639	28349.493
ST-MAI with F_credit (λ_1=1;Δ_Σ=120/20; $\Delta_{\gamma,c}$=0.01)	-7749.376	**28128.967**

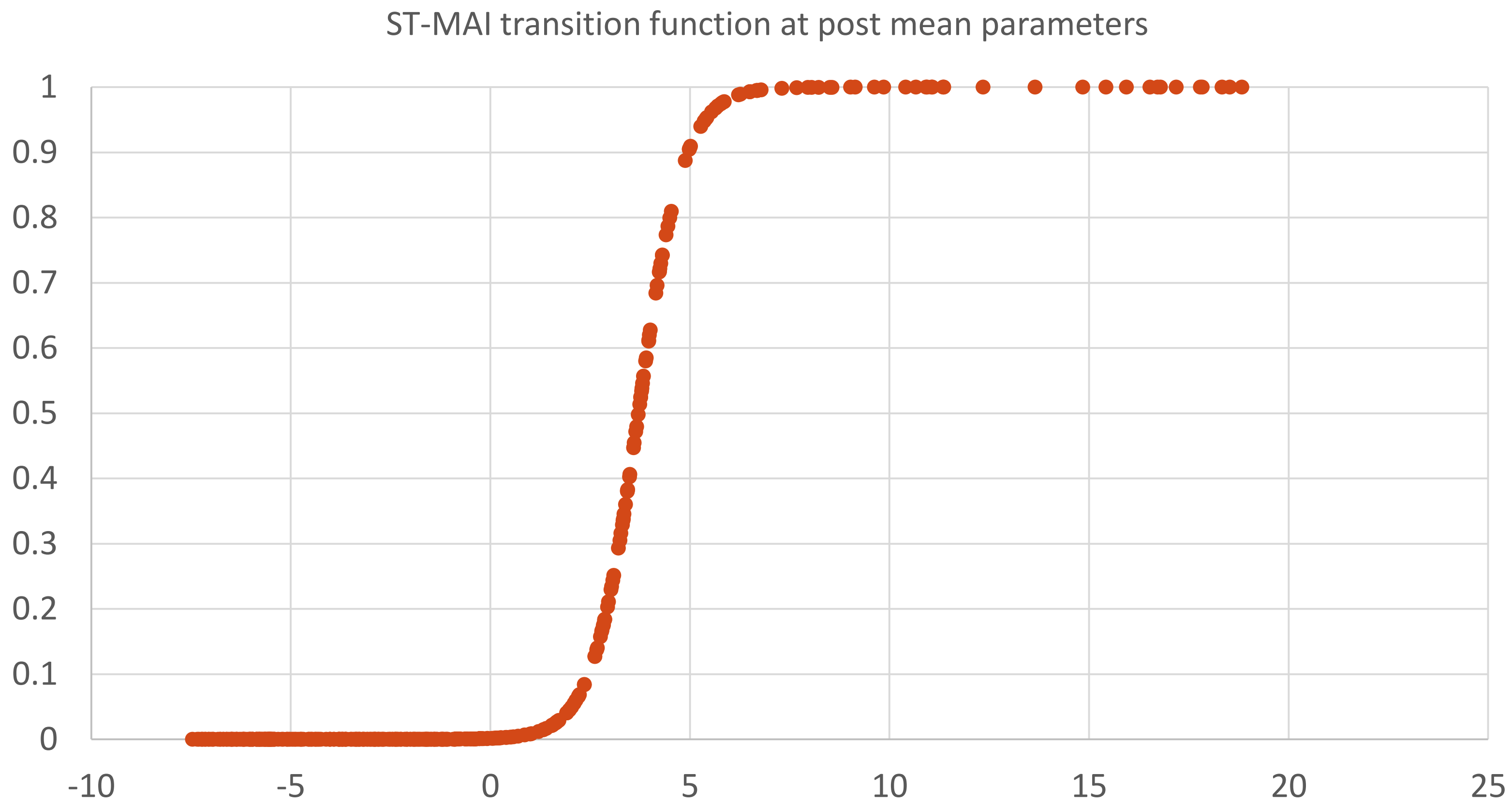
All with 4 factors. Hyperparameters are chosen to maximise the average likelihood and/or set acceptance rates to about 30%.

ST-MAI regimes



NBER recessions: greyish line.

Transition Function



ST-MAI B_matrix Post. Mean:

	F_activity	F_inflation	F_MonPol	F_credit
Employees nonfarm	1.00			
Avg hourly earnings	0.13			
Personal income	0.06			
Consumption	0.25			
Industrial Production	0.88			
Capacity utilization	0.85			
Unemp. Rate	-0.40			
Housing Starts	0.16			
CPI		1.00		
PPI		-0.09		
PCE deflator		0.52		
PPI ex food and energy		0.35		
FedFunds + shadow rate			1.00	
1year_rate			0.38	
EBP				1.00
BAA spread				0.28
Mortgage Spread				1.44
TED Spread				2.22
CommPaper Spread				2.14
Term Spread (10y-3mo)				-1.90

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

- To compute the transmission of these shocks we compute regime-dependent responses while allowing for regime-switching after the shock:

$$GR_{h,r}^{reg1} = 1/T_1 \sum_{t=1}^{T_1} GR_{h,r,t}^{(reg1)}(v_1^{(r)})$$

$$GR_{h,r}^{reg2} = 1/T_2 \sum_{t=1}^{T_2} GR_{h,r,t}^{(reg2)}(v_2^{(r)}),$$

where we split the set of histories $I_t = (Y_t', .., Y_{t-p+1}')'$ for $t = 1, .., T$ into $reg1$ and $reg2$ histories using the estimated transition function (regime 2 if $\Pi_t(\gamma, c, x_{t-1}) \geq 0.5$).

Computing Responses to Shocks IV

- The responses of Y to $v^{(r)}$ at horizon h conditional on history 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 $A = (A_1 ... A_p, D_1 ... D_p)'$

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 $GR_{h,r}^{reg2}$.

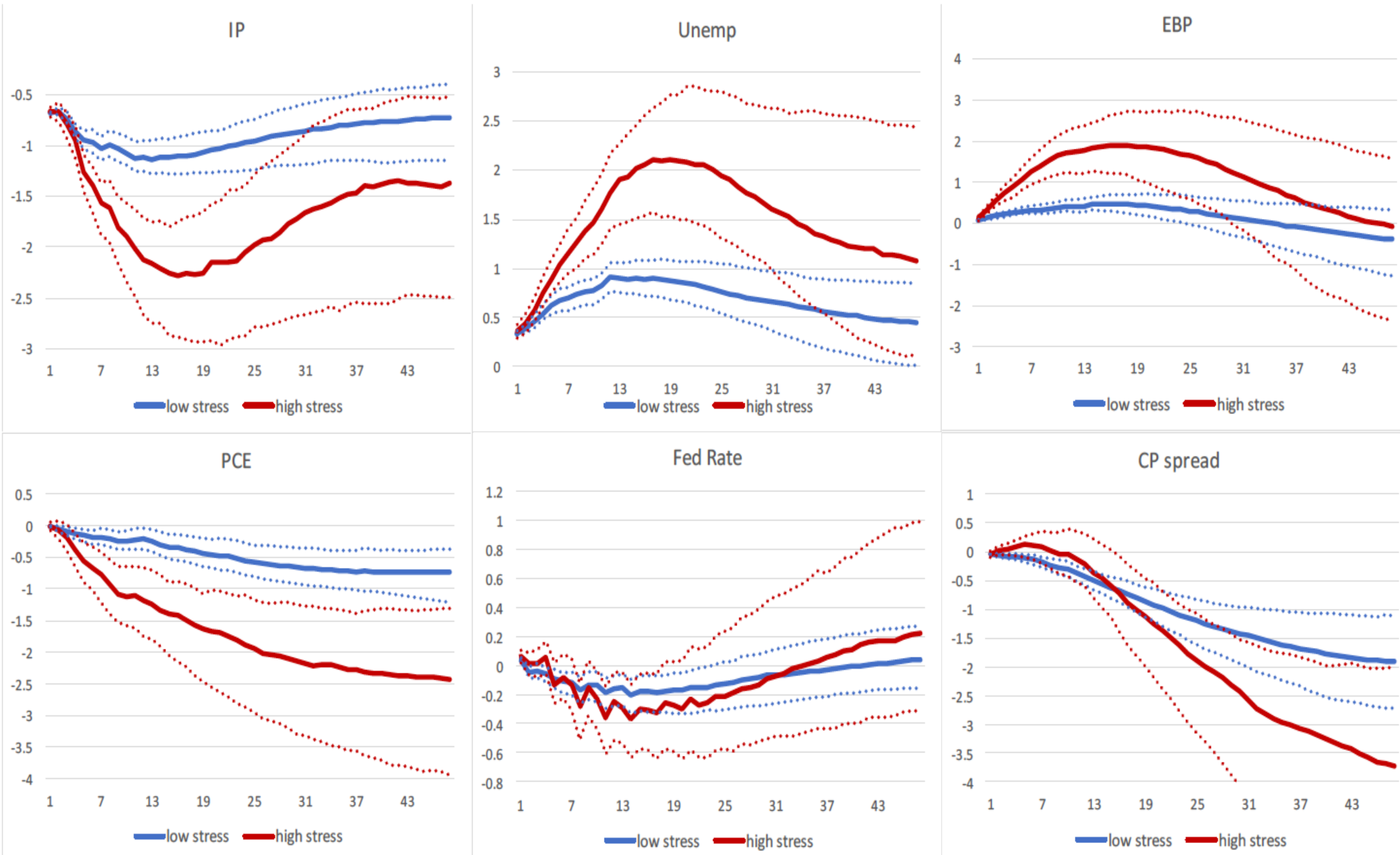
Computing Responses to Shocks VI

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 $h = 1, ..., H$.

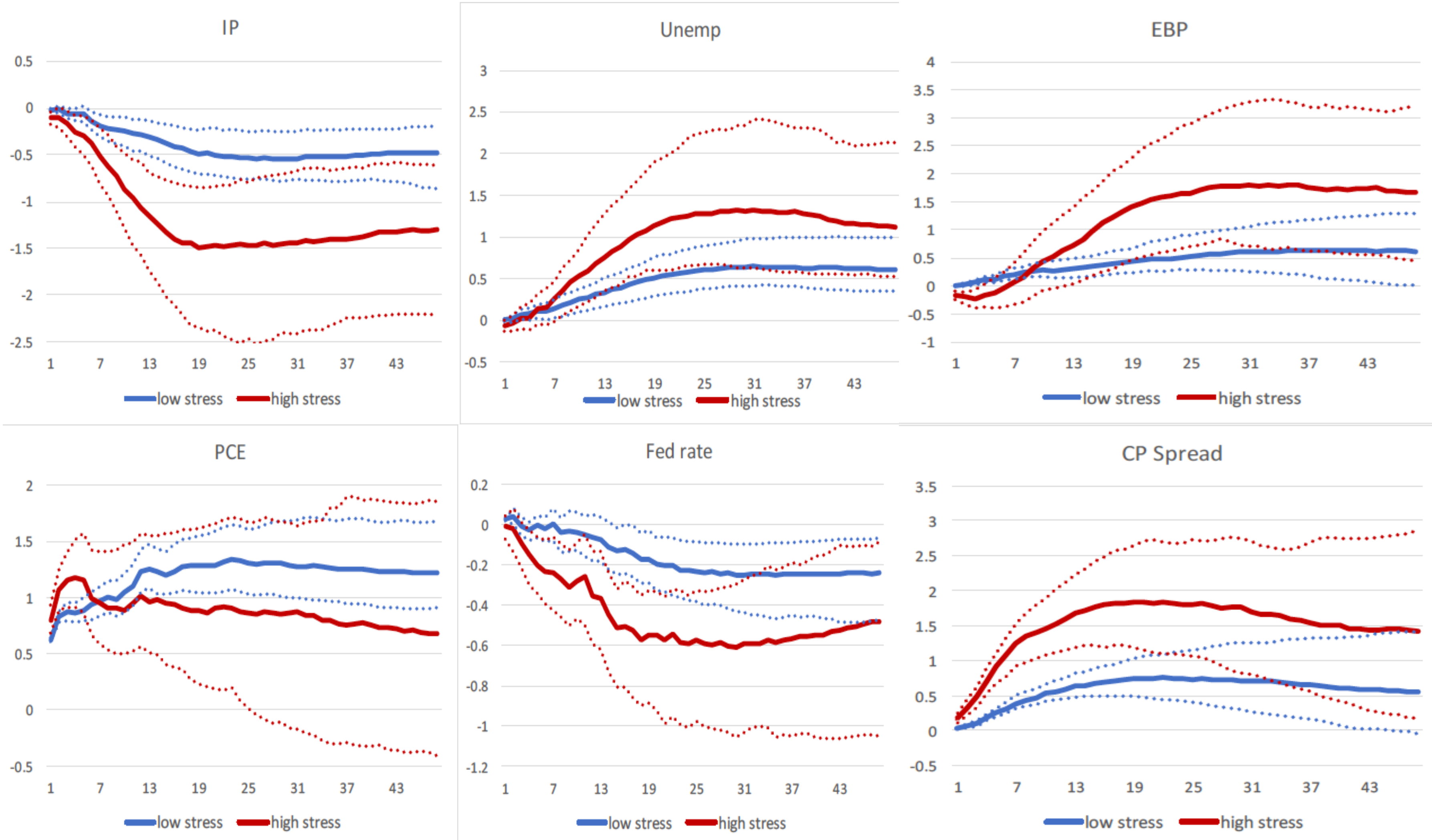
Responses computed for:

- Four common structural shocks.
- Negative shocks on economic activity:
  - Weak-demand (consumer and business lack of confidence, for example).
  - Price-pressure (a supply-type shock).
  - Monetary policy tightening.
  - Credit Stress (deterioration of credit conditions).
- Plots for key variables: Industrial Production, Unemployment, PCE inflation, EBP, Fed Rate, CP spread.
- All include 68% confidence bands. Cumulative responses.

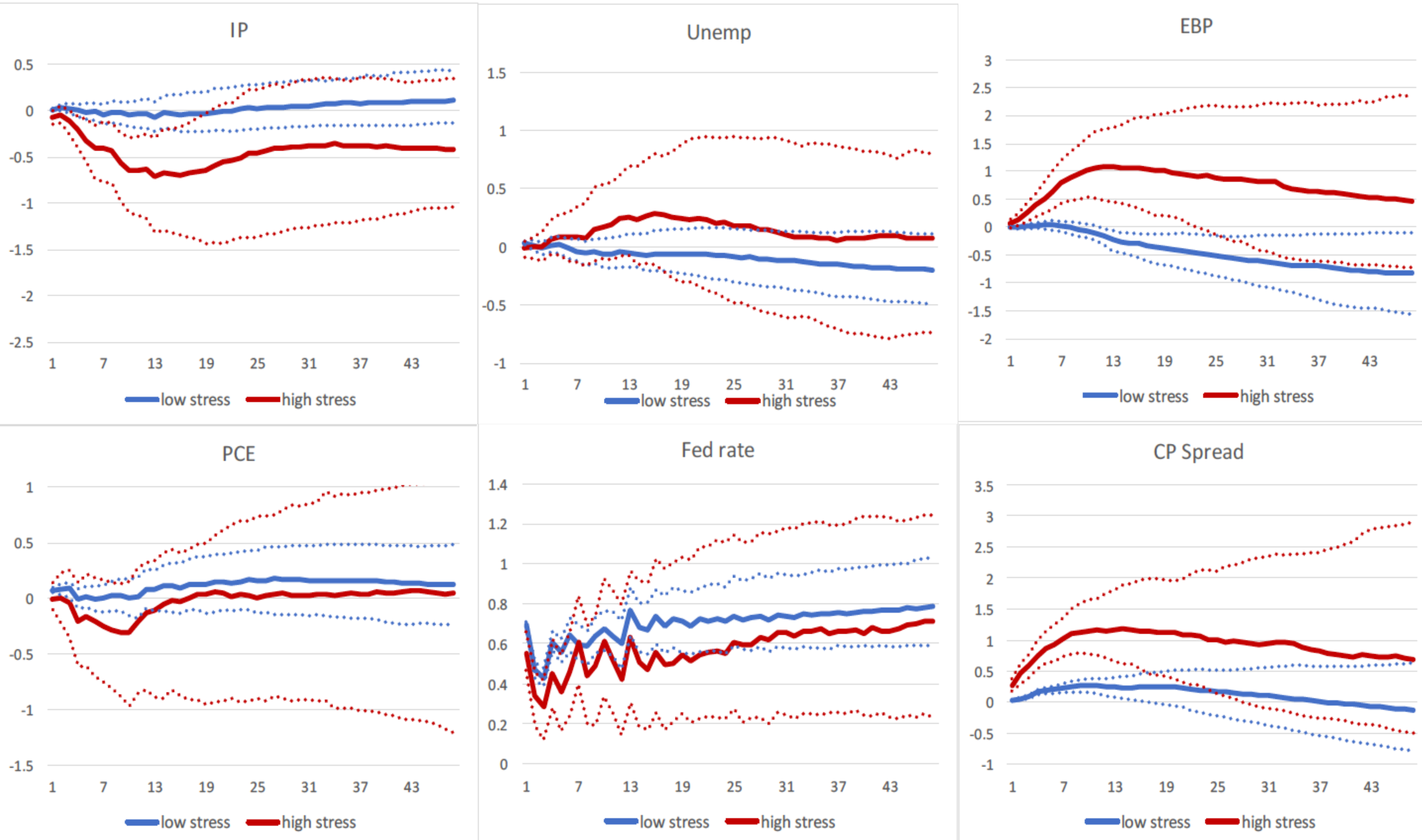
Responses to a Demand Shock



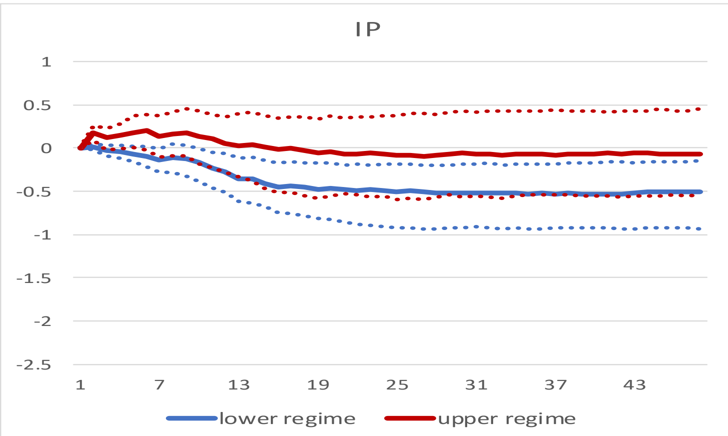
Responses to a Supply Shock

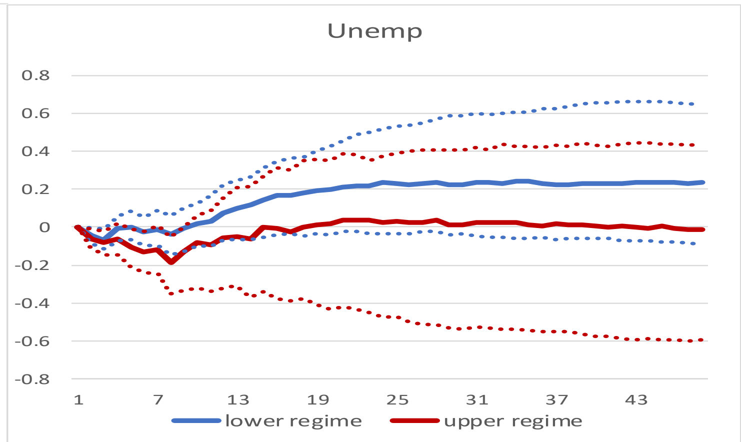


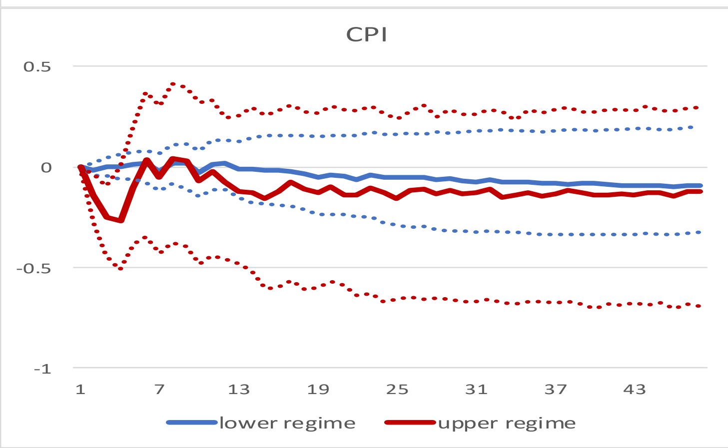
Responses to a MP shock

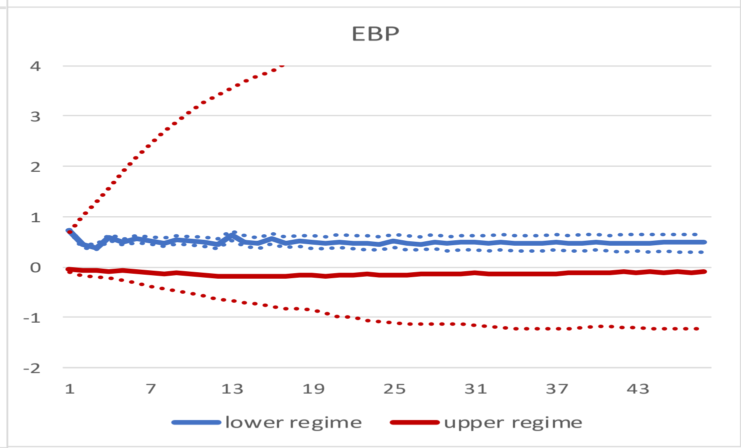


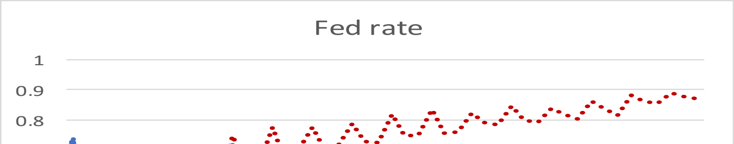
Response to a MP shock with a 5-variable STVAR:











In line with Caldara and Herbst (2019).

Large information set helps!

Responses to a Credit Shock

Comparing the Transmission of Positive and Negative Shocks

- We measure differences in the transmission of positive and negative shocks 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.
- We expect to find significant non-zero asymmetry for the high stress regime because the probability of regime changes (and nonlinear effects) is higher.

Comparing the Transmission of Small and Large Shocks

- We measure differences in the transmission of large and small shocks using

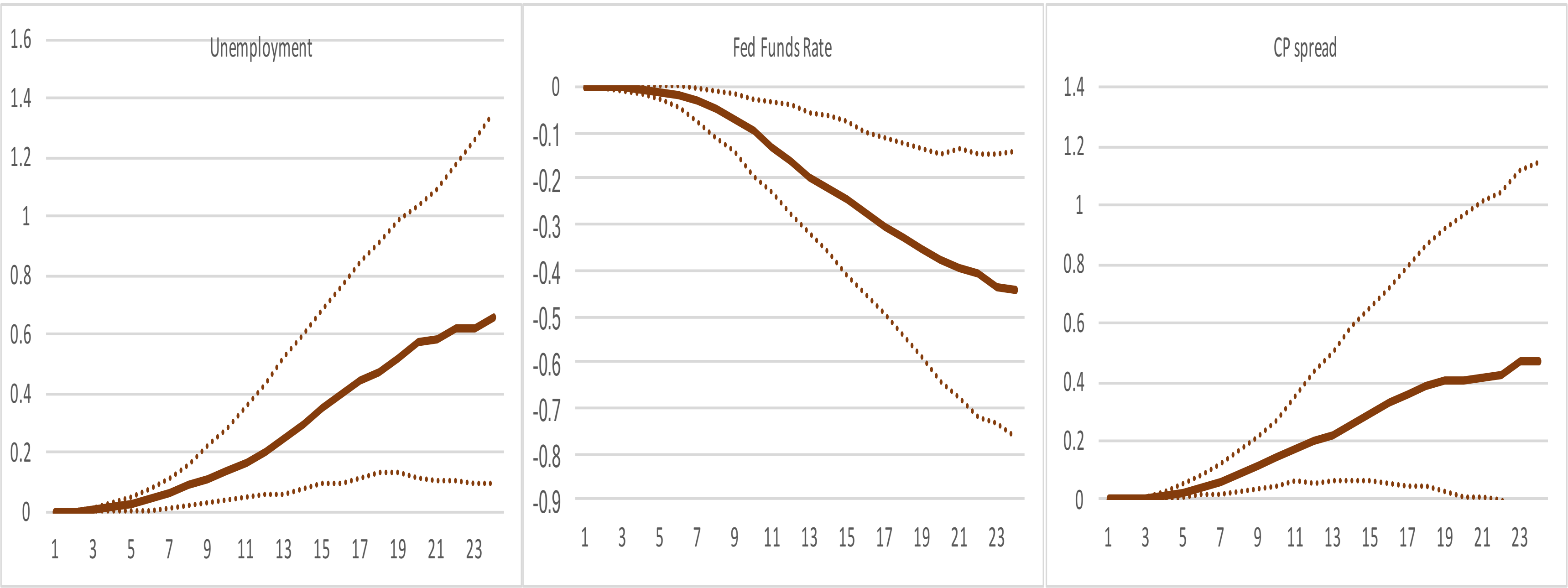
$$
\begin{aligned}
ASY_{h,r}^{ls(reg1)} &= 1/T_1 \sum_{t=1}^{T_1} \left[GR_{h,r,t}^{(reg1)}(2v_1^{(r)}) - 2 * GR_{h,r,t}^{(reg1)}(v_1^{(r)}) \right] \\
ASY_{h,r}^{ls(reg2)} &= 1/T_2 \sum_{t=1}^{T_2} \left[GR_{h,r,t}^{(reg2)}(2v_2^{(r)}) - 2 * GR_{h,r,t}^{(reg2)}(v_2^{(r)}) \right].
\end{aligned}
$$

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 use 68% bands to asssess this.

Probability of Staying in the High Stress Regime 12 months after the shock

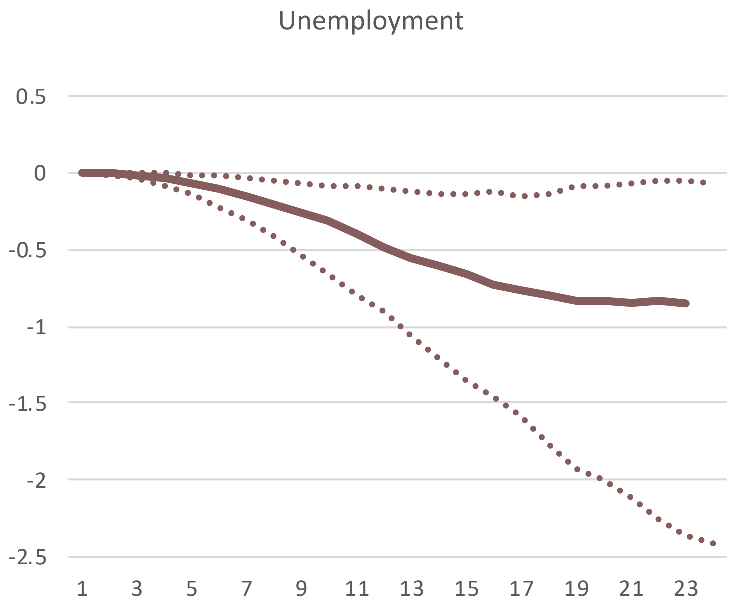
	Small (v_2)	Large ($2v_2$)
Positive Demand (activity) shock	**0.70**	**0.69**
Positive Supply (inflation) shock	**0.74**	**0.77**
Tightening of Monetary policy	**0.74**	**0.77**
Deterioration of Credit Conditions	**0.77**	**0.82**
	Small ($-v_2$)	**Large ($-2v_2$)**
Negative Demand (activity) shock	**0.72**	**0.72**
Negative Supply (inflation) shock	**0.67**	**0.64**
Easing of Monetary policy	**0.67**	**0.64**
Improvement of Credit Conditions	**0.64**	**0.58**

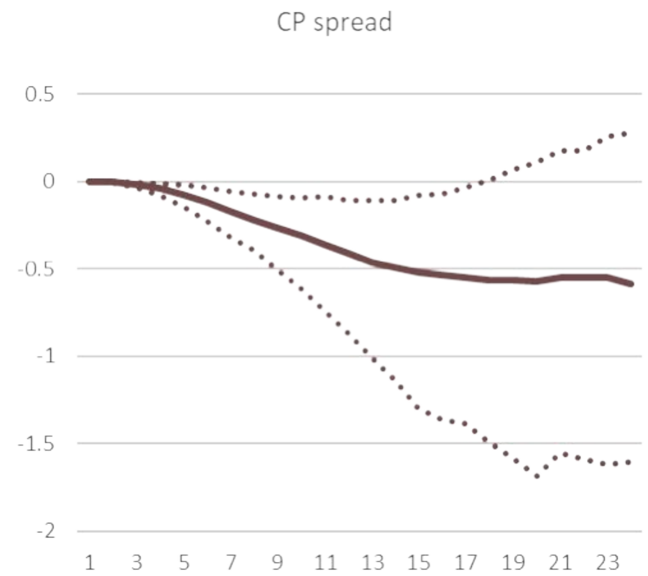
Large vs Small Inflationary shocks during high stress regime:



- Supply shocks that raise inflation lead to an increase in unemployment, a decline in the policy rate and an increase in the spread.
- These effects are further amplified if shock size are twice as large (credit shock are also similarly amplified).

Positive vs Negative MP shocks during high stress regime:





Easing of monetary policy has stronger effects on unemployment and CP spread than tightening of monetary policy. Similar effects for credit and supply shocks.

Conclusions I

- Smooth Transition MAI models are an effective new tool to find empirical evidence of amplification effects 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; negative shocks may have stronger effects than positive shocks; and large shocks may have disproportionate stronger effects than 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).