Measuring systemic financial stress and its impact on the macroeconomy[1]

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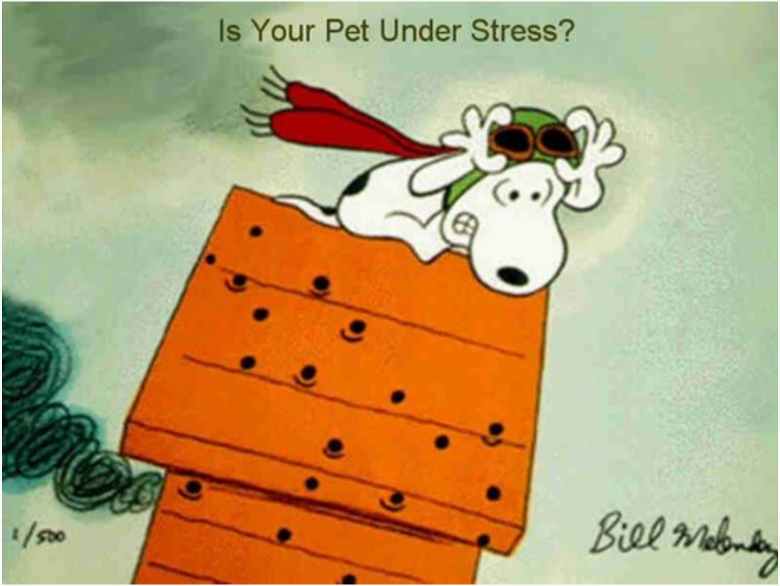
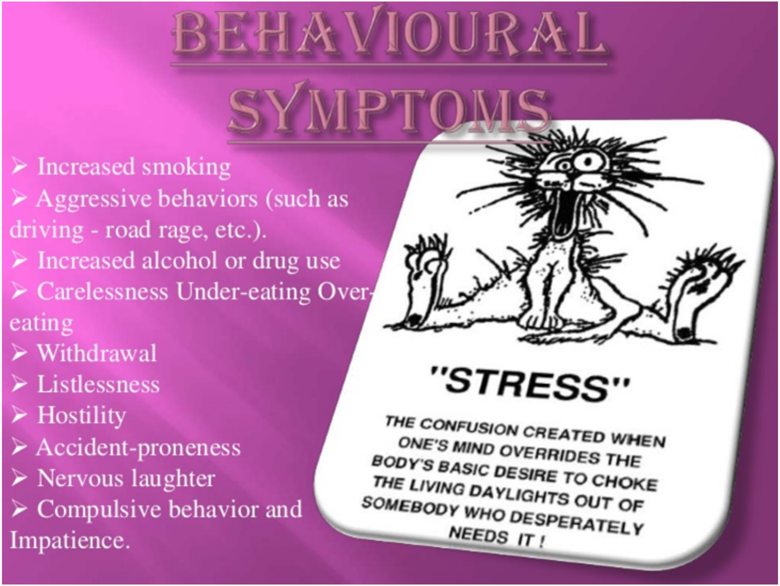
[1] The views expressed in this paper are our own and do not necessarily reflect the views of the ECB.

What is stress ...



... and how can we measure it?



What is financial stress?

- **(Mostly) unobservable root causes of financial stress:**
  - increased uncertainty (e.g., about asset valuations or the behaviour of other agents)
  - increased investor disagreement (differences of opinion)
  - stronger information asymmetries (intensifying problems related to adverse selection and moral hazard)
  - increased risk aversion, e.g. lower preferences for holding risky/illiquid assets (flight-to-quality / flight-to-liquidity)
- **Observable stress symptoms:**
  - increased market volatility; wider default and liquidity risk premia; market dry-ups for risky financial instruments; etc.

What the paper does

- **Proposes a general statistical framework for a systemic financial stress index (FSI)**
  - FSI aims to quantify the current state of instability in the financial system as a whole by aggregating a certain number of individual stress indicators into a single statistic
  - our framework nests several FSI designs proposed in the literature as special cases (incl. euro area CISS (Composite Indicator of Systemic Stress), the ECB's main FSI).
- **Focus on** *systemic stress* **such that the FSI can be interpreted as an** *ex post* **measure of** *systemic risk*
  - systemic risk defined as the risk that financial instability becomes so widespread that it impairs the functioning of a large part of the financial system with significant adverse effects on the broader economy
  - statistical framework derived from joint hypothesis that stress components are jointly high and strongly correlated
  - time-varying correlations operationalise idea of widespread stress.

What the paper does

- **Empirical application**
  - Computes CISS for the United States using data from 1973 to 2016
  - Proposes statistical inference procedures to test functional hypotheses for the FSI:
    - when does systemic stress become significantly different from zero or normal levels?
    - when are jumps in systemic stress significant?
  - Applies recently developed quantile vector autoregression (QVAR) model to estimate state-dependent dynamic effects of systemic stress on different measures of economic activity for the US.

Related Literature (Selective)

- **Systemic risk measures**
  - **systemic risk of financial institutions**: Brownlees and Engle (2017), Brunnermeier and Adrian (2016), Billio et al. (2012)
  - **financial stress indices**: Illing and Liu (2006), Hakkio and Keeton (2009), Oet et al. (2011), Brave and Butters (2011), Carlson, Lewis and Nelson (2012), Blix Grimmaldi (2010, 2011), Hollo, Kremer and Lo Duca (2012), Garcia-de-Andoain and Kremer (2016), van Roye (2011), Caldarelli et al. (2009), Vermeulen et al. (2015).
- **Real effects of financial crises/stress/systemic risk**
  - **descriptive approach**: Laeven and Valencia (2008, 2012), Taylor and Schularick (2012), Romer and Romer (2016)
  - **predictive regressions**: Giglio, Kelly and Priutt (2016)
  - **VARs**: Hubrich and Tetlow (2012), Hartmann, Hubrich, Kremer and Tetlow (2015), Kremer (2016).

General Framework

- Assume there exists an $N \times 1$ vector of individual stress factors $\boldsymbol{z}_t$ measuring stress in certain financial market segments, all increasing in the level of stress.
- Systemic stress defined as a "Joint Hypothesis Problem"

$\mathcal{H}_{(1)t}$	:	stress factors $\boldsymbol{z}_t$ highly co-move
$\mathcal{H}_{(2)t}$	:	stress factors $\boldsymbol{z}_t$ are jointly high (co-extremeness)
	$\Downarrow$	
Systemic Stress	:	$\mathcal{H}_t \equiv \{\mathcal{H}_{(1)t} \wedge \mathcal{H}_{(2)t}\}$.

General Definition of Systemic Stress Index

- For $l \in (1,2)$, let $\mathcal{H}_{(l)t}$ be a hypothesis formalised with $N \times N$ bounded real-valued matrix function $\mathcal{G}_{(l)t}$ of the vector of stress factors $\boldsymbol{z}_t$. Then a systemic stress index $\mathcal{S}_t$ can be defined as a statistic for the joint hypothesis $\mathcal{H}_t \equiv \left\{\mathcal{H}_{(1)t} \wedge \mathcal{H}_{(2)t}\right\}$, given by

$$\mathcal{S}_t \equiv \frac{1}{N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} \left(\mathcal{G}_{(1)t}\right)_{ij} \left(\mathcal{G}_{(2)t}\right)_{ji} . \tag{1}$$

- $\mathcal{S}_t$ is a scaled matrix association index proposed by Mantel (1967) extensively used in different fields of science to model similarity across data observed in a matrix form (e.g., Moran's I or Geary's C measuring geographical distance).
- In our case, index shows to what extent stress factors $\boldsymbol{z}_t$ jointly co-move and are jointly high by associating two matrix functions $\mathcal{G}_{(1)t}$ and $\mathcal{G}_{(2)t}$ that quantify the extent of co-movement and joint extremeness of $\boldsymbol{z}_t$.

Homogenisation - Stress Factors

- Each raw stress indicator x_{it} transformed using conditional empirical cumulative distribution function (normalised ranks)

$$z_{it} = \begin{cases} \frac{1}{T_0-1}\sum_{s=1}^{T_0-1}\mathcal{I}(x_{is} \leq x_{it}), & \text{for} \quad t = 1, \ldots, T_0 - 1, \\ \frac{1}{t}\sum_{s=1}^{t}\mathcal{I}(x_{is} \leq x_{it}), & \text{for} \quad t = T_0, \ldots, T, \end{cases}$$

  where $\mathcal{I}(\cdot)$ is the indicator function and T_0 the start date of recursive transformation (such that future data is ignored in the updating).
- Resulting stress factors z_{it} homogenised
  - in terms of scale: $z_{it} \in (0, 1]$
  - in terms of distribution: z_{it} taken as standard uniform random variable $z_{it} \sim U(0, 1)$.

Co-movement

- Co-movement is measured vis-à-vis median state

$$\tilde{\mathcal{Z}}_t = (\boldsymbol{z}_t - 0.5\boldsymbol{\imath}_N)(\boldsymbol{z}_t - 0.5\boldsymbol{\imath}_N)'$$

- Conditional autoregressive covariance matrix (following Exponentially Weighted Moving Average (EWMA) model)

$$\mathcal{H}_t = \pi_{(1)}\mathcal{H}_{t-1} + \left(1 - \pi_{(1)}\right)\tilde{\mathcal{Z}}_t, \quad \text{for} \quad t = 1, \ldots, T,$$

- Conditional autoregressive correlation matrix $\mathcal{G}_{(1)t}$ with elements

$$\left(\mathcal{G}_{(1)t}\right)_{ij} = \frac{(\mathcal{H}_t)_{ij}}{\sqrt{(\mathcal{H}_t)_{ii}(\mathcal{H}_t)_{jj}}} \in [-1, 1]$$

  which are time-varying Spearman rank correlation coeffients.
- Smoothing coefficient constant at $\pi_{(1)} = 0.93$ for weekly data.

Co-Extremeness

- Conditional autoregressive co-extremeness matrix

$$\mathcal{G}_{(2)t} = \pi_{(2)}\mathcal{G}_{(2)t-1} + \left(1 - \pi_{(2)}\right)\mathcal{Z}_t, \quad \text{for} \quad t = 1, \ldots, T,$$

  with $\mathcal{Z}_t = \boldsymbol{z}_t \boldsymbol{z}_t'$
- $\mathcal{G}_{(2)t}$ reaches its maximum when $\mathcal{Z}_t = \boldsymbol{\imath}_N \boldsymbol{\imath}_N'$, i.e. when each stress factor is at its maximum, and its minimum when $\mathcal{Z}_t = \mathbf{O}_N$, i.e. when each stress factor is at its minimum.
- Smoothing coefficient constant at $\pi_{(2)} = 0.93$ for weekly data
- CISS indicator (Hollo, Kremer and Lo Duca, 2012) sets $\pi_{(2)} = 0$ (no smoothing, stress factors z_{it} set at their actual values observed in t.

Systemic Financial Stress Index

- Countable set of raw stess indicators $\boldsymbol{x}_t \equiv (x_{1t}, \dots, x_{Nt})'$, transformed into stress factors $\boldsymbol{z}_t \equiv (z_{1t}, \dots, z_{Nt})'$
- Co-movement quantified by $\mathcal{G}_{(1)t}$
- Co-extremeness quantified by $\mathcal{G}_{(2)t}$

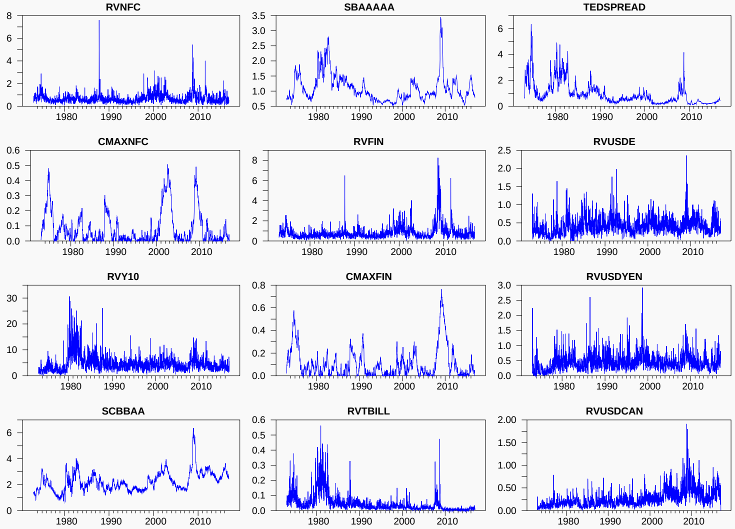
$$\Downarrow$$

Scaled Matrix Association Index

$$\mathcal{S}_t\left(\pi_{(1)}, \pi_{(2)}\right) = \frac{1}{N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} \left(\mathcal{G}_{(1)t}(\pi_{(1)})\right)_{ij} \left(\mathcal{G}_{(2)t}(\pi_{(2)})\right)_{ji},$$

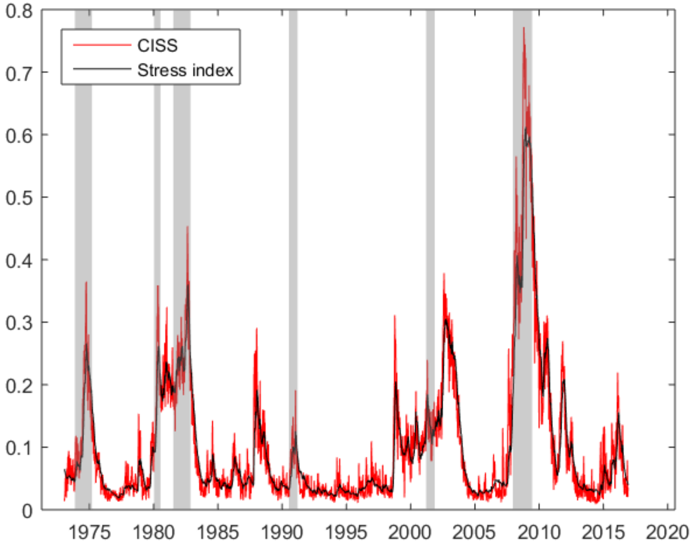
with $\pi_{(1)}$ and $\pi_{(2)}$ set at 0.93.

Raw Stress Indicators for the US Financial System



Notes: rv - realised variance; nfc - nonfinancial corp.; fin - financial corp.; cmax - max. cumulative loss over 2y window.

Systemic Financial Stress Index for the US



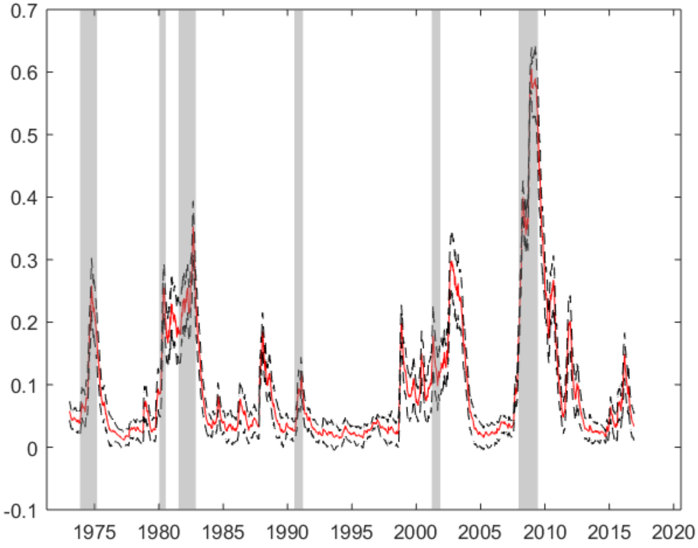
Statistical Inference

- Assume the following regression model holds:

$$\mathcal{S}_{ijt} \quad = \quad \mathcal{S}_t + u_{ijt}, \quad i, j = 1, \ldots, N,$$

  where $\mathcal{S}_{ijt} = \left(\mathcal{G}_{(1)t}(\pi_{(1)})\right)_{ij} \left(\mathcal{G}_{(2)t}(\pi_{(2)})\right)_{ji}$ and the random variables u_{ijt} satisfy the standard regularity conditions.
- We propose a bootstrap procedure to test certain functional hypothesis such as confidence bands for levels and changes (jumps) in the stress index
  - Given $\hat{\mathcal{S}}_t$, sample residuals $\left(\hat{u}_{ijt}^{(l)}, \quad i, j = 1, \ldots, N\right)_{l=1}^{M}$,
  - Generate sample $\mathcal{S}_{ijt}^{(l)} = \hat{\mathcal{S}}_t + u_{ijt}^{(l)}$,
  - Construct functionals of $\mathcal{S}_{ijt}^{(l)}$.

Stress Index with estimated confidence bands $\alpha = 0.05$



Real Effects of Financial Stress in a QVAR

- Systemic financial crises generally associated with severe contractions in real economic activity
- This may suggest a non-linear empirical relationship between financial stress and economic activity
- Specifically, we hypothesise that the conditional dynamic effects of financial stress on economic activity are particularly strong when financial stress shocks are particularly high
- Hypothesis tested within quantile VAR (QVAR) framework using quantile impulse response functions (QIRFs) as recently developed in Chavleishvili and Manganelli (2017) and Chavleishvili (2017)
- QVAR as a statistical tool for simultaneous modelling of the conditional distribution of a multiple time series
  - can be seen as a generalisation of the univariate approach by Giglio, Kelly and Pruitt (2016).

Robust predictive power of the CISS - further evidence

- Why should CISS be included in conventional "monetary policy VARs"?
- Previous studies (e.g., Kremer, 2016) suggest CISS to contain signficant and robust (in-sample) predictive power for economic activity (and some other macro variables)
- We apply Granger-causal-priority (GCP) tests for variable selection in VARs recently developed by Jarocinski and Mackowiak (REStat, 2016)
- Tests for GCP encompass both direct and indirect effects, while Granger-noncausality tests only consider direct effects (in higher-dimensional VARs)
- In a VAR, y_i is GCP to y_j if it is possible to partition all variables in y into two subsets, y_I and y_J, such that $y_i \subseteq y_I$, $y_j \subseteq y_J$, and y_J does not Granger-cause y_I

Granger-causal-priority tests

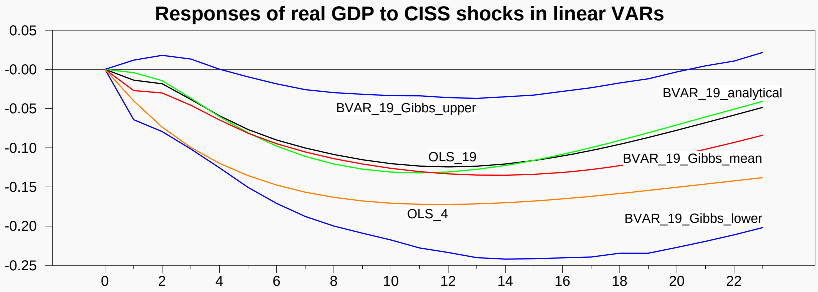
- The Bayesian GCP test procedure is based on a closed-form expression of the posterior probability that a vector of variables of interest y_I is Granger-causally-prior to a variable y_j included in a broader set of variables y_J
- For instance, in our application, we have $N_I = 3$ variables of interest in y_I (inflation, real GDP growth, federal funds rate) and $N_J = 16$ other potential VAR variables
- Evaluating the posterior of GCP is then consistent with multiple partitions of y_J: there are 2^{N_J-1} models consistent with the Null and 2^{N_J-1} models consistent with the alternative, such that the set of all models on which the GCP tests are conditioned includes $2^{N_J-1} + 2^{N_J-1} = 2^{N_J} = 2^{16} = 65536$ elements
- Posterior computed as ratio of two sums of Bayes factors from all relevant restricted and unrestricted models

Results from Granger-causal-priority tests

Table: Posterior probabilities that inflation, real GDP growth, and the fed funds rate are not jointly Granger-causally-prior to variable *j*

j	variable	exact	rank	MC3 simulation	rank
(1)	CISS	1.0000	1	1.0000	1
(2)	NFCI (Chicago Fed stress index)	1.0000	1	0.9998	10
(3)	term spread	1.0000	1	0.9998	10
(4)	corporate bond spread (BAA)	1.0000	1	0.9999	6
(5)	Ted spread	1.0000	1	0.9997	13
(6)	stock return volatility (S&P 500)	0.9999	13	0.9999	6
(7)	stock price growth (S&P 500)	1.0000	1	1.0000	1
(8)	base money growth	1.0000	1	0.9999	6
(9)	M1 growth	0.9961	15	0.9977	15
(10)	M2 growth	0.7729	16	0.7816	16
(11)	bank loan growth	0.9999	13	0.9998	10
(12)	housing starts growth	1.0000	1	0.9995	14
(13)	capacity utilisation	1.0000	1	1.0000	1
(14)	unemployment rate	1.0000	1	1.0000	1
(15)	non-farm payroll growth	1.0000	1	0.9999	6
(16)	retail sales growth	1.0000	1	1.0000	1

Financial stress effects in large vs. small linear VARs



Notes: IRFs from OLS (4 and 19 variables) and from BVARs (19 variables) with analytical and simulated (Gibbs sampler) posteriors.

Modelling the conditional distribution Quantile Impulse Response Functions (QIRFs)

- Fundamentals $\boldsymbol{y}_t$ are subject to shocks $\varepsilon_t \sim i.i.d.\mathcal{N}(\mathbf{0}, \Sigma)$.
- $\boldsymbol{y}_t$ are asymmetric
  - Requires modelling of the entire conditional distribution instead of modelling the conditional mean function only
- Framework developed by Chavleishvili (2017)
  - Quantile specific responses in VARs
  - Dynamic linear conditional quantile function as the main statistical tool

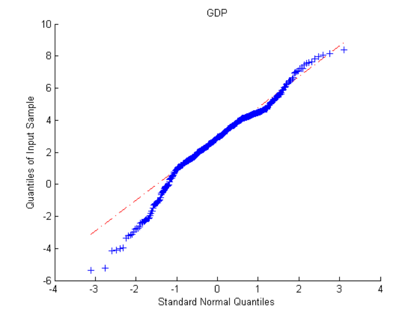
$$\begin{aligned}
\Pr[y_{it} < \mathcal{Q}_{y_{it}|\boldsymbol{z}_{t-1}}(\tau)] &= \tau, \quad i = 1, \dots K, \\
\tau &\in (0,1), \\
\boldsymbol{z}_{t-1} &\equiv (\boldsymbol{y}'_{t-1}, \boldsymbol{y}'_{t-2}, \dots, \boldsymbol{y}'_{t-p})', \\
\mathcal{Q}_{y_{it}|\boldsymbol{z}_{t-1}} &= \phi(\tau) + \boldsymbol{\Phi}(\tau)\boldsymbol{z}_{t-1}.
\end{aligned}$$

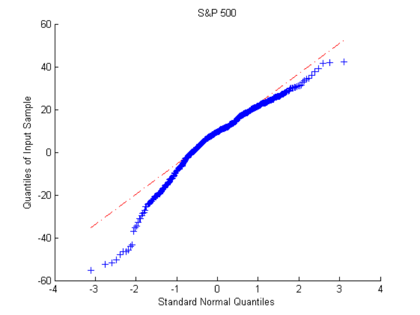
  - Impact of the financial stress shock for $h=1,2,\dots$

$$\begin{aligned}
\boldsymbol{\Delta}_{\mathcal{Q}_{\boldsymbol{y}_{t+h}|\boldsymbol{z}_t}} &= \mathrm{E}\left[\mathcal{Q}_{\boldsymbol{y}_{t+h}|\boldsymbol{z}_t} | \varepsilon_{it} = F^{-1}_{\varepsilon_{it}}(\tau)\right] - \mathrm{E}\left[\mathcal{Q}_{\boldsymbol{y}_{t+h}|\boldsymbol{z}_t}\right], \\
F_{\varepsilon_{it}}(\cdot) &:= \text{Empirical distribution function.}
\end{aligned}$$

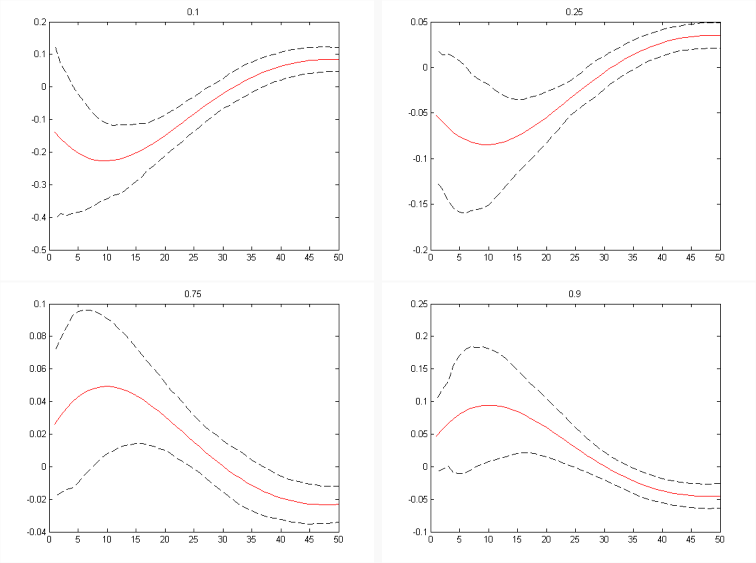
Empirical results

- Monthly QVAR(1) with $\boldsymbol{y}_t = (\mathcal{S}_t, i_t, r_t, x_t, \pi_t)'$. $\mathcal{S}_t$ is the financial stress index, i_t is the federal funds rate and r_t, x_t, π_t, u_t are annual growth rates of the S&P 500 price index, real GDP, consumer price index and unemployment rate.





QIRFs for real GDP growth to financial stress shocks



Concluding Remarks

- **We propose a semi-parametric approach to a financial stress index which ...**
  - is easy to compute and update
  - is robust to outliers and distributional assumptions
  - takes explicit account of the systemic dimension of financial stress.
- **We propose a new tool to estimate the joint dynamic conditional distribution of financial stress and macroeconomic fundamentals**
  - confirms idea of particularly strong real effects of financial stress when stress is high
  - future research: systematic comparison with alternative non-linear approaches.

Uses of the CISS in policy applications

- **CISS has become a widely used indicator of the overall state of financial (in)stability**
  - weekly updates available on ECB homepage (SDW) and commercial dataproviders (e.g., Bloomberg, Datastream)
- **Macro-prudential policy**
  - Tool for regular financial stability surveillance (see, e.g., the financial stability reports of ECB, Sveriges Riksbank, Banco de España, Banco de Portugal)
  - For some countries, CISS among set of indicators found useful to assess the release of counter-cyclical capital buffers
- **Monetary policy**
  - CISS as leading business cycle indicator due to its average predictive content: "average" $\rightarrow$ linear relationship
  - CISS may provide early warning on the likely amplified impact of financial stress on the real economy: "crisis times" $\rightarrow$ non-linear relationship.

Composite Indicator of Systemic Stress, CISS

- Countable set of raw stess indicators $\boldsymbol{x}_t \equiv (x_{1t}, \dots, x_{Nt})'$, transformed into stress factors $\boldsymbol{z}_t \equiv (z_{1t}, \dots, z_{Nt})'$
- Co-movement quantified by $\mathcal{G}_{(1)t}$

$$\Downarrow$$

CISS

$$\mathcal{S}_t\left(\pi_{(1)}\right) = \frac{1}{N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} \left(\mathcal{G}_{(1)t}(\pi_{(1)})\right)_{ij} \left(\boldsymbol{z}_t \boldsymbol{z}_t'\right)_{ji},$$

$$\mathcal{S}_t\left(\pi_{(1)}\right) = \frac{1}{N^2} \boldsymbol{z}_t' \mathcal{G}_{(1)t}(\pi_{(1)}) \boldsymbol{z}_t,$$

with $\pi_{(1)}$ set at 0.93.

QIRFs for stock returns to financial stress shocks