Melting Down: Systemic Financial Instability and the Macroeconomy

Manfred Kremer

with Philipp Hartmann, Kirstin Hubrich (all ECB) and Robert J. Tetlow (Federal Reserve Board)

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Introduction

- **Financial crises are rare disruptive events which challenge macro model building and forecasting**
  - **Economic history is replete with financial crises, although they still represent rare events in typical macro data samples (for developed economies).**
  - **Systemic financial crises, i.e. crises in which financial instability spreads widely across the entire financial system, are particularly disruptive, often causing huge losses in output and social welfare.**
  - **Financial and real shocks generated by a financial crisis seem to give rise to abrupt and unusual (non-linear) changes in economic dynamics, likely caused by certain amplification, propagation and feedback mechanisms activated during times of distress.**

Introduction (cont'd)

- **Recently growing literature on theoretical macro-financial models that incorporate financial instability**
  – Brunnermeier and Sannikov (AEA 2014), He and Krishnamurthy (RES 2011), Boissay, Collard and Smets (JPE 2015).
- **Few empirical contributions on crisis effects**
  – Schularick and Taylor (AEA 2012), Giglio, Kelly and Pruitt (NBER 2015), Hubrich and Tetlow (JME 2015).
- **This paper presents estimates of a small-scale macro-financial VAR model for the euro area that**
  – allows independent regime shifts in coefficients and shock variances to capture potential non-linearities;
  – integrates features of systemic financial instability by using a composite indicator of systemic stress (CISS) as one of the endogenous model variables.

Preview of main results

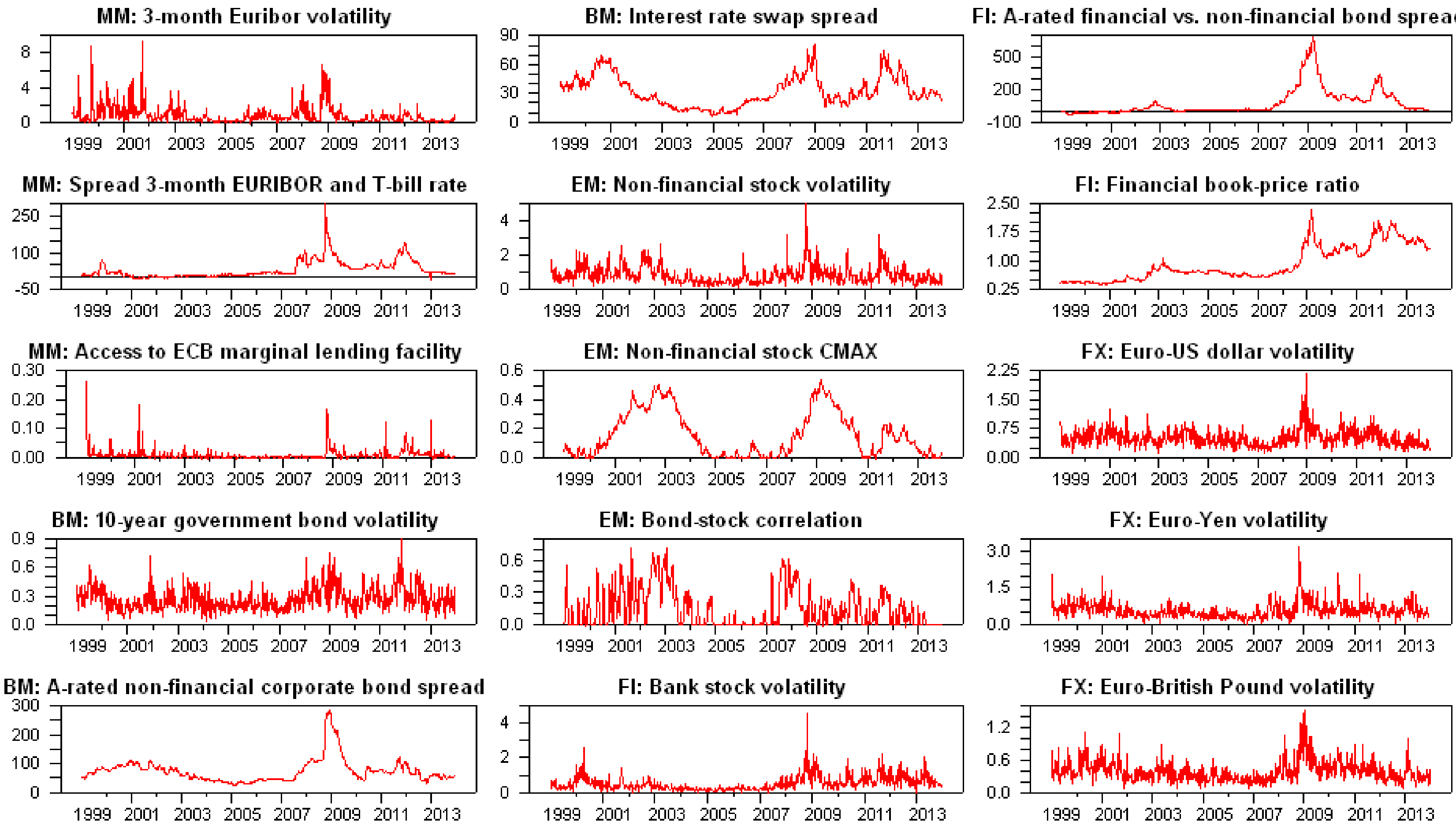
- **We find strong evidence for non-linearities**
  - **Both the variances of shocks and the model coefficients characterising the dynamic relationships between the variables undergo recurrent regime changes;**
  - **Developments in the CISS help interpreting the identified regimes;**
  - **Effects of shocks in the CISS on economic activity become much larger during high-stress regimes.**

Outline

1. Measuring systemic financial instability: The ECB's CISS
2. Markov-Switching Bayesian Vector Autoregression (MS-BVAR) model
3. Determining and interpreting macroeconomic regimes
4. From subprime turmoil to the systemic meltdown: A model tale
5. Concluding remarks

1. CISS as measure of systemic stress

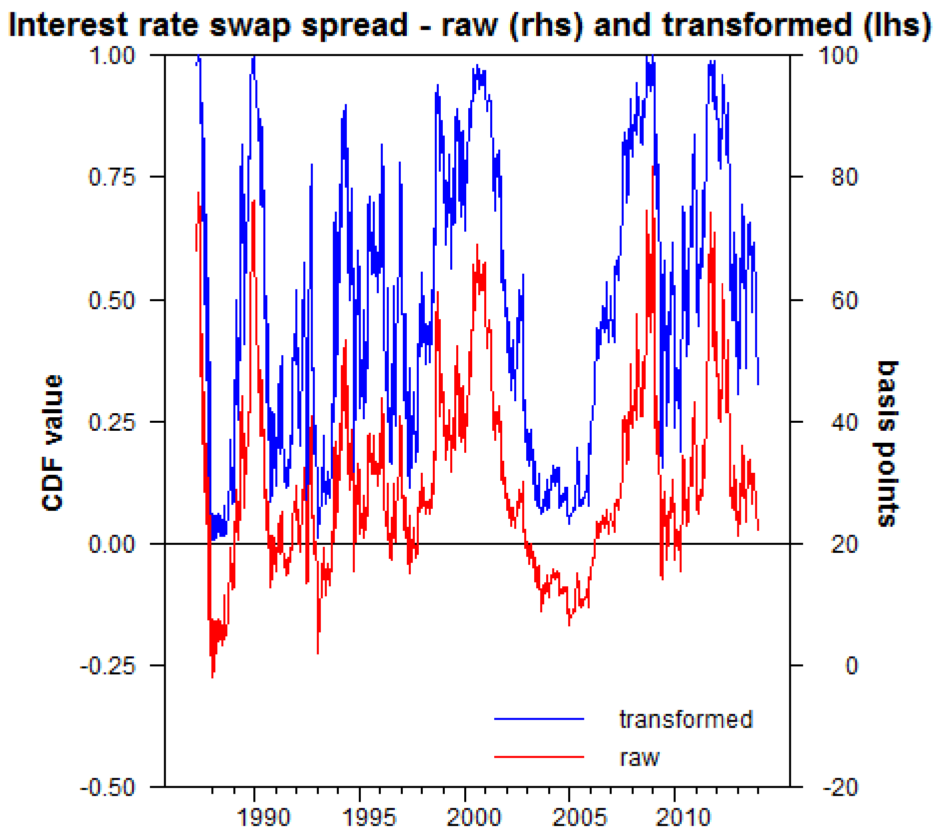
•"You can't see the wood for the trees"

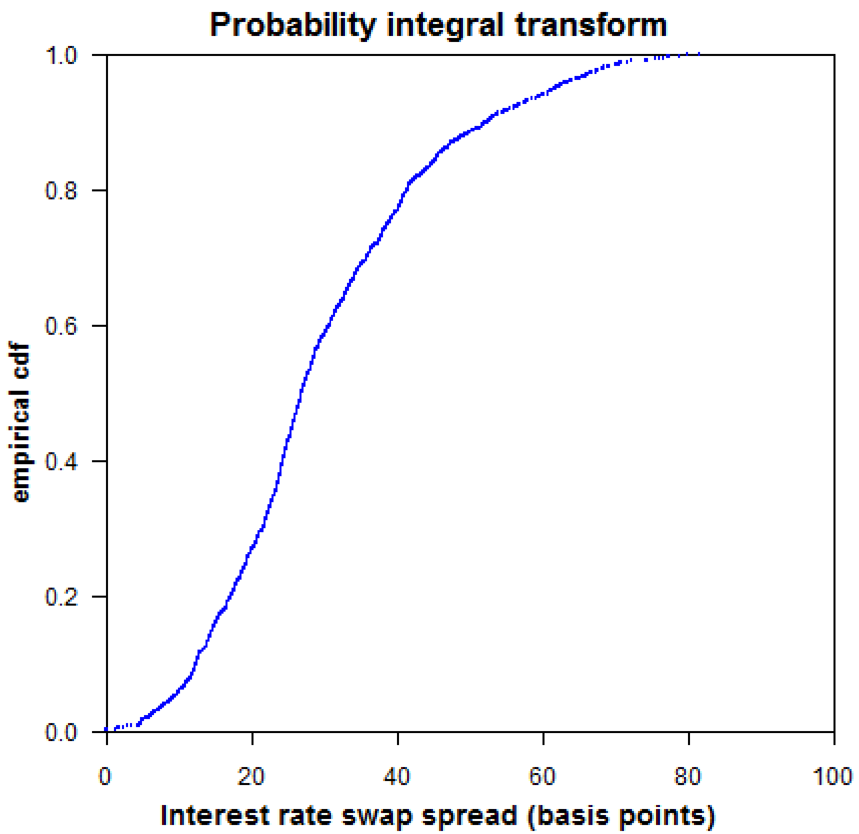


1. CISS as measure of systemic stress (cont'd)

- ECB's Composite Indicator of Systemic Stress (Hollo, Kremer and Lo Duca, 2012);
- Novel financial stress index which builds on standard definitions of systemic risk (focus on *widespread* financial instability);
- Identifies 5 key segments of financial system: 1) Financial intermediaries; 2) Money market; 3) Bond market; 4) Stock market; 5) Foreign exchange market;
- Populates each of the 5 segments with 3 representative standard price-based stress indicators (incl. volatilities, spreads, cumulated valuation losses, etc.);
- Raw indicators transformed by empirical CDF (probability integral transform) to harmonise scale [0, 1] and distribution (std. uniform)
- Compute 5 subindexes of stress by taking arithmetic averages;
- Main innovation: aggregate subindexes based on the time-varying rank correlations between them (analogue to computation of portfolio risk from asset return variances and covariances)
  - Puts more weight on situations of *widespread* instability.

- **Probability integral transform: example case**





1. CISS - Portfolio-theoretic aggregation framework

- **Individual indicators aggregated into composite indicator based on portfolio theory**
  - **Compute system-wide stress analogous to portfolio risk in a static CAPM framework**
  - **Simple *two*-asset example:**

$$\sigma_p^2 = w_1^2\sigma_1^2 + w_2^2\sigma_2^2 + 2w_1w_2\rho\sigma_1\sigma_2$$

  - **General *n*-asset case:**

$$\sigma_p^2 = \sum_{i=1}^n \sum_{j=1}^n w_i w_j \operatorname{cov}_{ij} = \sum_{i=1}^n \sum_{j=1}^n w_i w_j \rho_{ij}\sigma_i\sigma_j$$

$$= w'\Sigma w \qquad\qquad = (w \circ \sigma)'\Omega(w \circ \sigma)$$

Σ a variance - covariance matrix and Ω a correlation matrix

1. CISS - Portfolio-theoretic aggregation framework

- **Applied to the present context:**
  - replace asset risk (σ_i) with transformed individual stress measures (s_i);
  - portfolio risk (σ_p^2 or σ_p) then yields our composite stress index (CISS).

- **Two avenues to introduce systemic risk features:**
  - time-varying cross-correlations collected in correlation matrix Ω_t
    $\Rightarrow$ *widespread instability, interconnectedness*
  - segment-specific "market shares" $w_{i,t}$ in the "portfolio" of stress measures $s_{i,t}$
    $\Rightarrow$ *systemic importance* (size, flows, real impact, …).

1. CISS formula

$$CISS_t = (w_t \circ s_t)'\Omega_t(w_t \circ s_t) \quad \in (0,1] \qquad \text{or}$$
$$= \sqrt{(w_t \circ s_t)'\Omega_t(w_t \circ s_t)}$$

$$w_t^{segments} = (w_{MM,t}, w_{BM,t}, w_{EM,t}, w_{FI,t}, w_{FX,t})'$$
$$= (\overline{w}_{MM}, \overline{w}_{BM}, \overline{w}_{EM}, \overline{w}_{FI}, \overline{w}_{FX})' = (0.19,\ 0.22,\ 0.14,\ 0.25,\ 0.20)'$$

$$s_t = \left(s_{MM,1,t}, s_{MM,2,t}, s_{MM,3,t}, s_{BM,1,t}, s_{BM,2,t}, s_{BM,3,t}, \cdots s_{FX,2,t}, s_{FX,3,t}\right)' \quad \text{is a } 1\times 15 \text{ vector}$$
$$w_t = 1/3 \cdot \left(\overline{w}_{MM}, \overline{w}_{MM}, \overline{w}_{MM}, \overline{w}_{BM}, \overline{w}_{BM}, \overline{w}_{BM}, \cdots \overline{w}_{FX}, \overline{w}_{FX}, \overline{w}_{FX}\right)' \quad \text{is a } 1\times 15 \text{ vector}$$

$$\Omega_t = \begin{pmatrix} 1 & \rho_{1,2,t} & \cdots & \rho_{1,15,t} \\ \rho_{12,t} & 1 & & \rho_{2,15,t} \\ \vdots & \cdots & \cdots & \vdots \\ \rho_{1,15,t} & \rho_{2,15,t} & \cdots & 1 \end{pmatrix} \quad \text{is a } 15\times 15 \text{ matrix}$$

1. CISS - Time-varying cross-correlations

- **Time-varying cross-correlations**
  - **computed as exponentially weighted moving averages (EWMA):**
  - **time-varying version of Spearman's rank correlation.**

$$\sigma_{ij,t} = \lambda \sigma_{ij,t-1} + (1-\lambda)\tilde{s}_{i,t}\tilde{s}_{j,t}$$

$$\sigma^2_{i,t} = \lambda \sigma^2_{i,t-1} + (1-\lambda)\tilde{s}^2_{i,t}$$

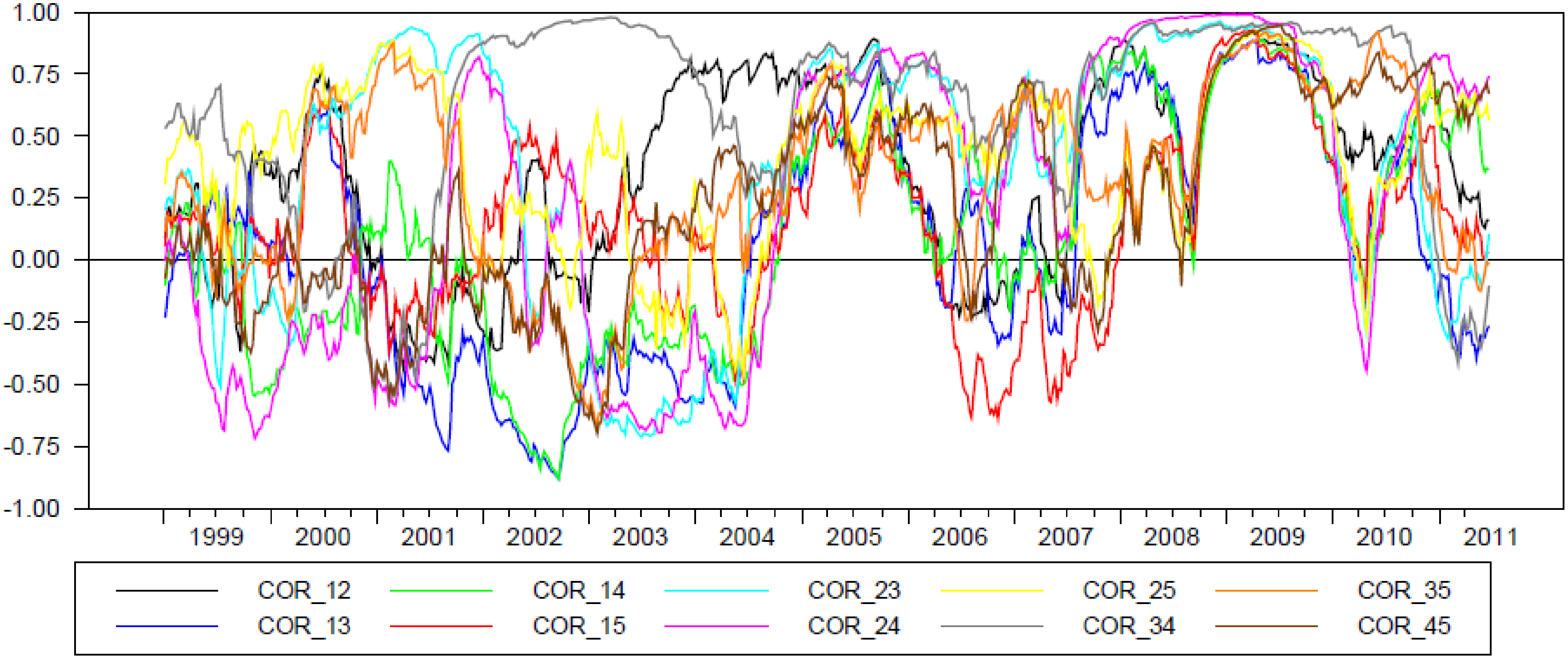
$$\rho_{ij,t} = \sigma_{ij,t} / \sigma_{i,t}\sigma_{j,t}$$

$$\tilde{s}_{i,t} = (s_{i,t} - 0.5)$$

$$\lambda = 0.93$$

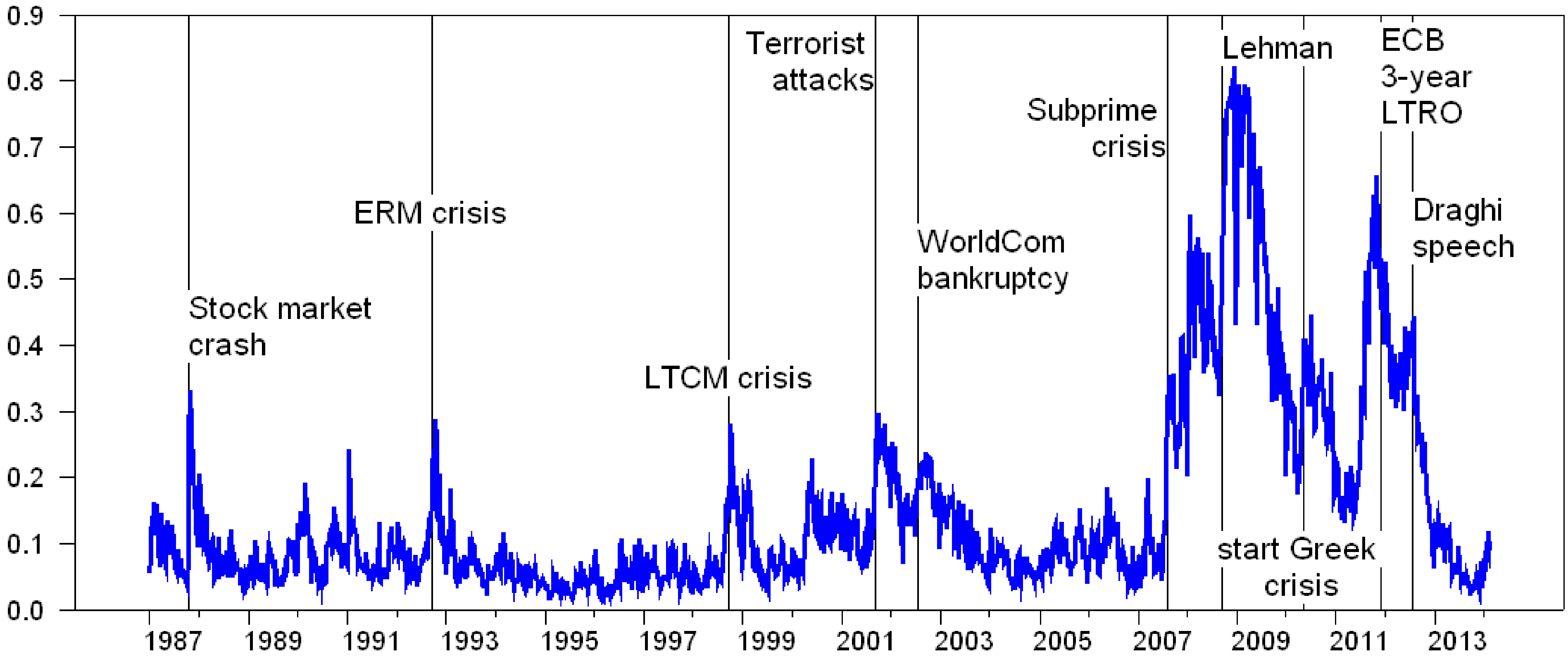
1. CISS - Time-varying cross-correlations

Fig. 2. Cross-correlations between subindices



Notes: Correlation pairs are computed as exponentially-weighted moving averages with smoothing parameter λ=0.93. The cross-correlations are labelled as follows: 1 – money market, 2 – bond market, 3 – equity market, 4 – financial intermediaries, 5 – foreign exchange market. Weekly euro area data from 8 Jan. 1999 to 24 June 2011.

1. CISS and financial stress events, 1987 to 2010



2. MS-BVAR model setup

- Endogenous variables: $y_t = [\Delta IP_t, \Delta P_t, R_t, \Delta Ln_t, S_t]$
  - ΔIP_t: growth rate of industrial production
  - ΔP_t: inflation rate (HICP)
  - R_t: money market rate (3-month Euribor)
  - ΔLn_t: growth rate of bank lending
  - S_t: CISS
- Identification
  - Choleski decomposition, ordering of variables as above
  - Systemic financial stress responds instantaneously to innovations in all other variables (but not vice versa)
  - Results robust to other orderings
- Data sample: Euro area
  - monthly frequency, at annual rates
  - January 1987 to December 2010
  - seasonally adjusted

3. Determining macroeconomic regimes

Table 1:

Types of regime changes	no changes	variance change		coefficient change	variance and coefficient change	
Number of regimes	1v1c	2v1c	3v1c	1v2c	2v2c	3v2c
Log MDD	-6.05	92.36	131.95	37.76	126.08	147.36
Diff. to constant parameter model (1v1c)	0.00	98.41	138.00	43.81	132.13	153.41

Notes: Log Marginal data densities (mdd) are calculated as in Sims, Waggoner and Zha (2008); 1v1c: constant parameter model; ivjc: i shock variance regimes, j coefficient regimes.

Conclusions

- **There are significant regime shifts**
- **Preferred specification has 3 variance and 2 coefficient regimes**

3. Interpreting regimes: variance regimes

Table 2:

Regime label	production	inflation	interest rate	loans	CISS
1: v1	1.000	1.000	1.000	1.000	1.000
2: v2	0.905	1.525	0.285	0.738	0.617
3: v3	0.853	1.994	0.645	0.563	2.980
Notes: Standard deviation of the first variance regime (v1) normalised to one by construction.					

Conclusions

- **No uniform ranking order of shock volatilities across variables**
- **But regime v3 associated with very large financial stability shocks**

3. Interpreting regimes: descriptive statistics

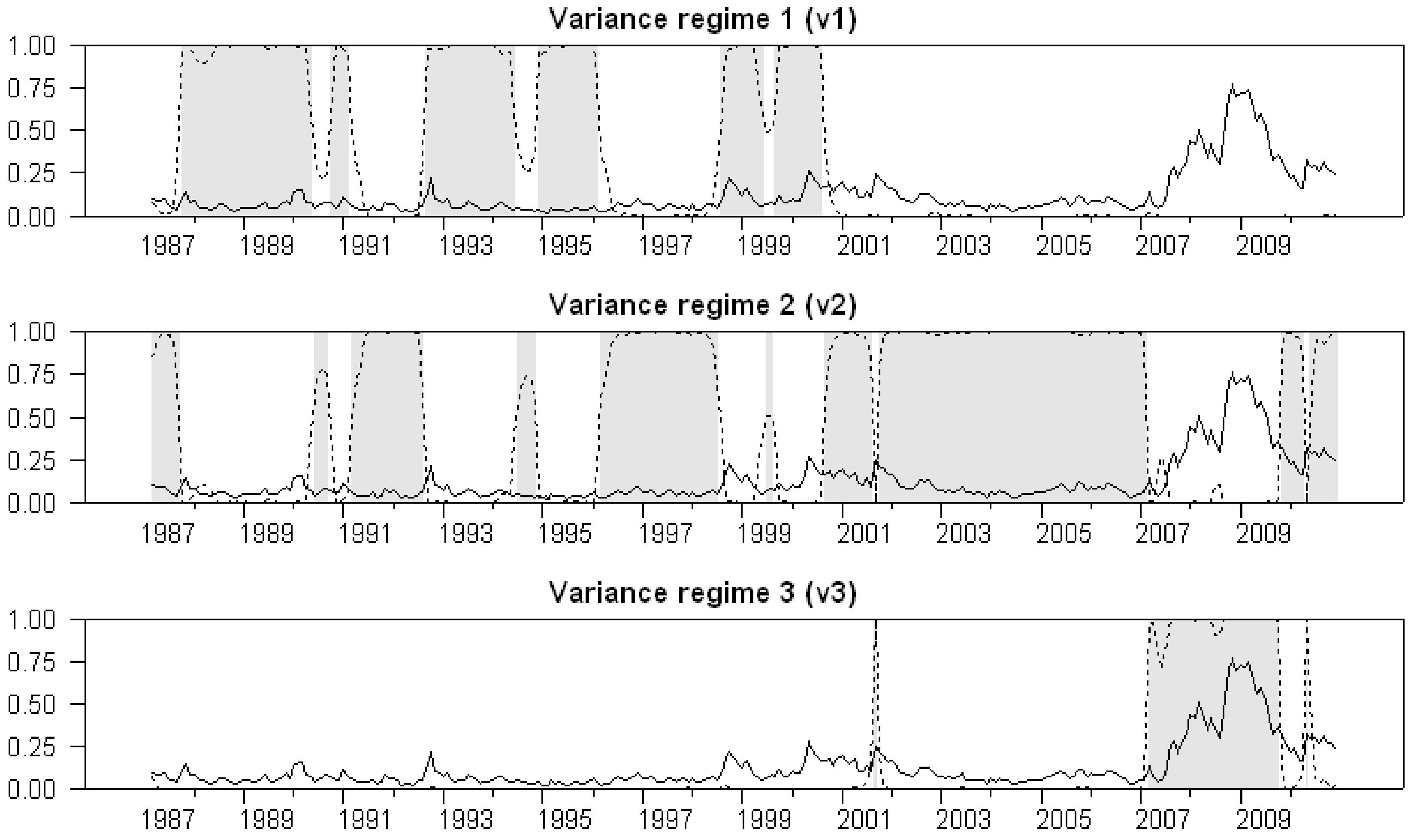
Table 3:

Regime label	Conditional means					sample shares
	production	inflation	interest rate	loans	CISS	
1: v1, c1	0.535	2.264	5.850	5.973	0.071	16.1%
2: v1, c2	3.391	3.007	6.130	8.426	0.092	17.8%
3: v2, c1	2.783	1.959	3.219	6.325	0.081	35.3%
4: v2, c2	1.163	2.834	5.850	6.108	0.110	18.9%
5: v3, c1	3.958	2.430	4.178	9.658	0.260	5.2%
6: v3, c2	-11.293	1.571	2.878	4.655	0.520	6.6%

Notes: v=variance regime (1, 2, or 3); c=coefficient regime (1 or 2)

- **Regime 6 stands out: highest reading for CISS, lowest for all other variables**

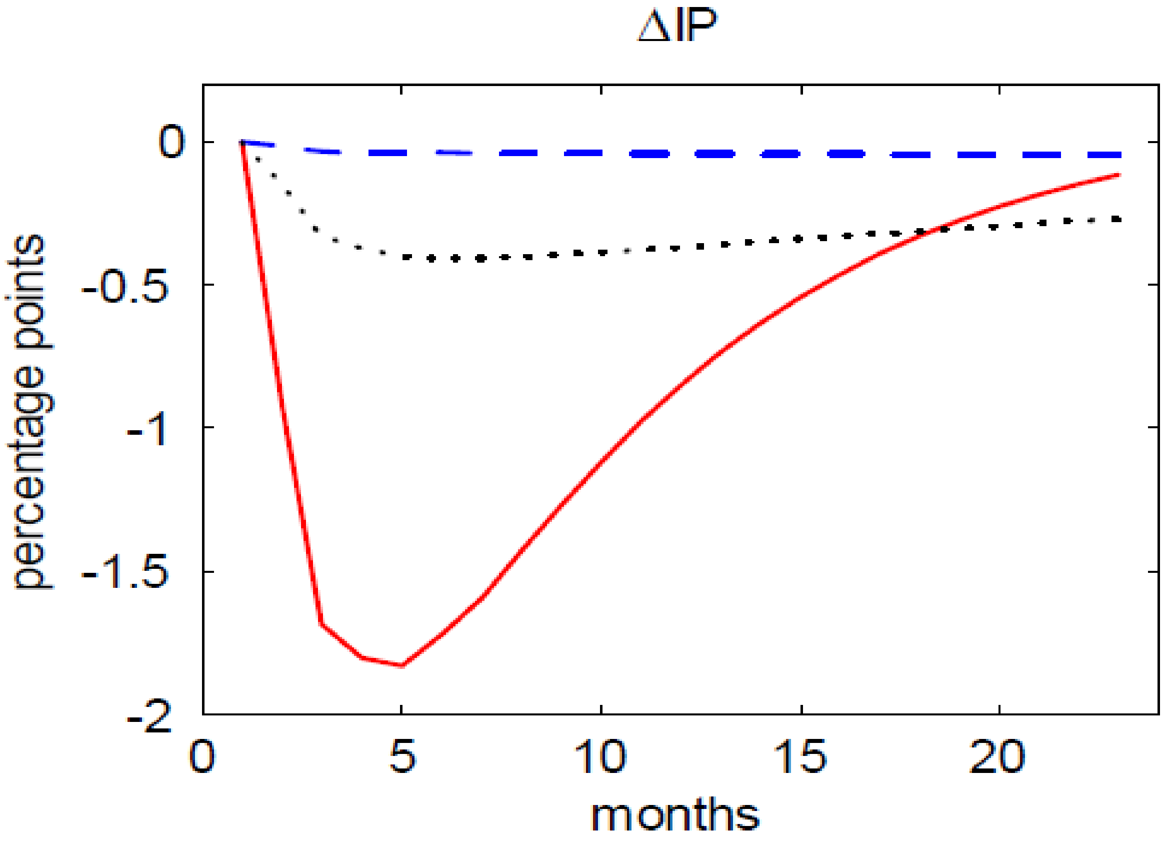
3. CISS and variance regime probabilities
(dominant regimes shaded)



3. Industrial production growth and coefficient regime probabilities *(dominant regimes shaded)*

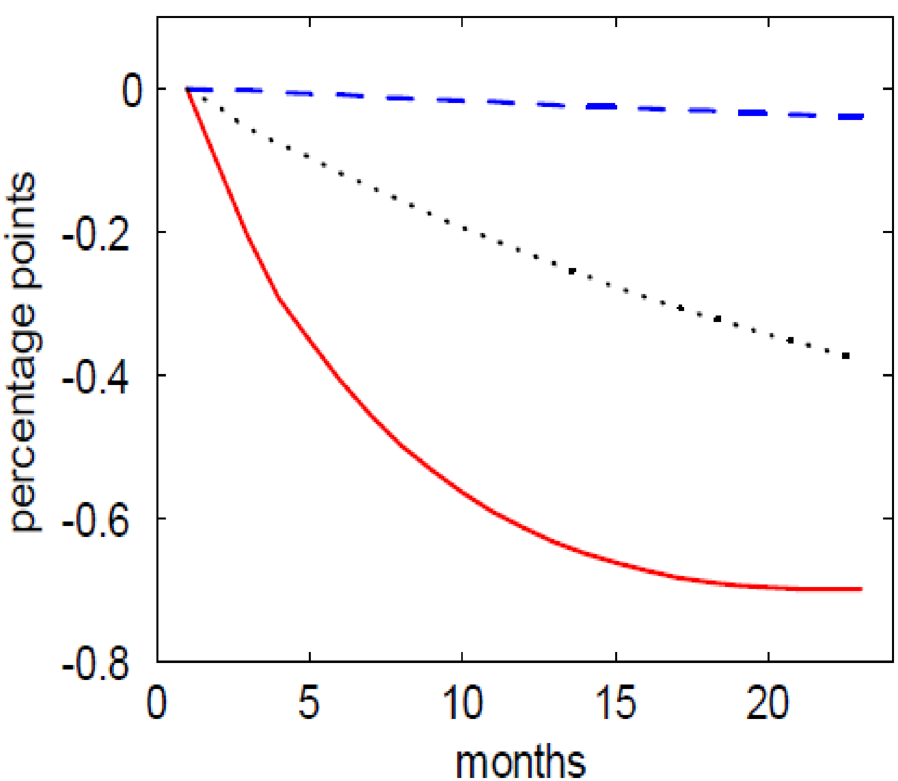
3. Impulse response functions: output growth to CISS shocks

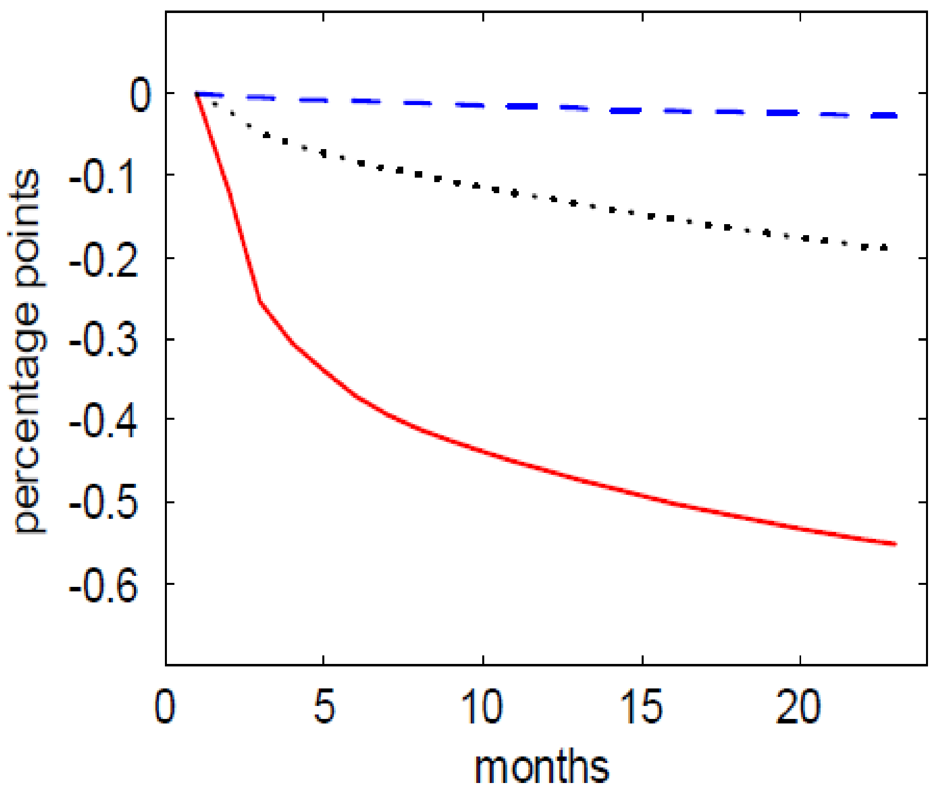
"systemic crisis" regime 6 (red solid line)
"tranquil times" regime 1 (blue dashed line)
linear VAR (black dotted line)



3. Impulse response functions: short rate and loans to CISS shocks

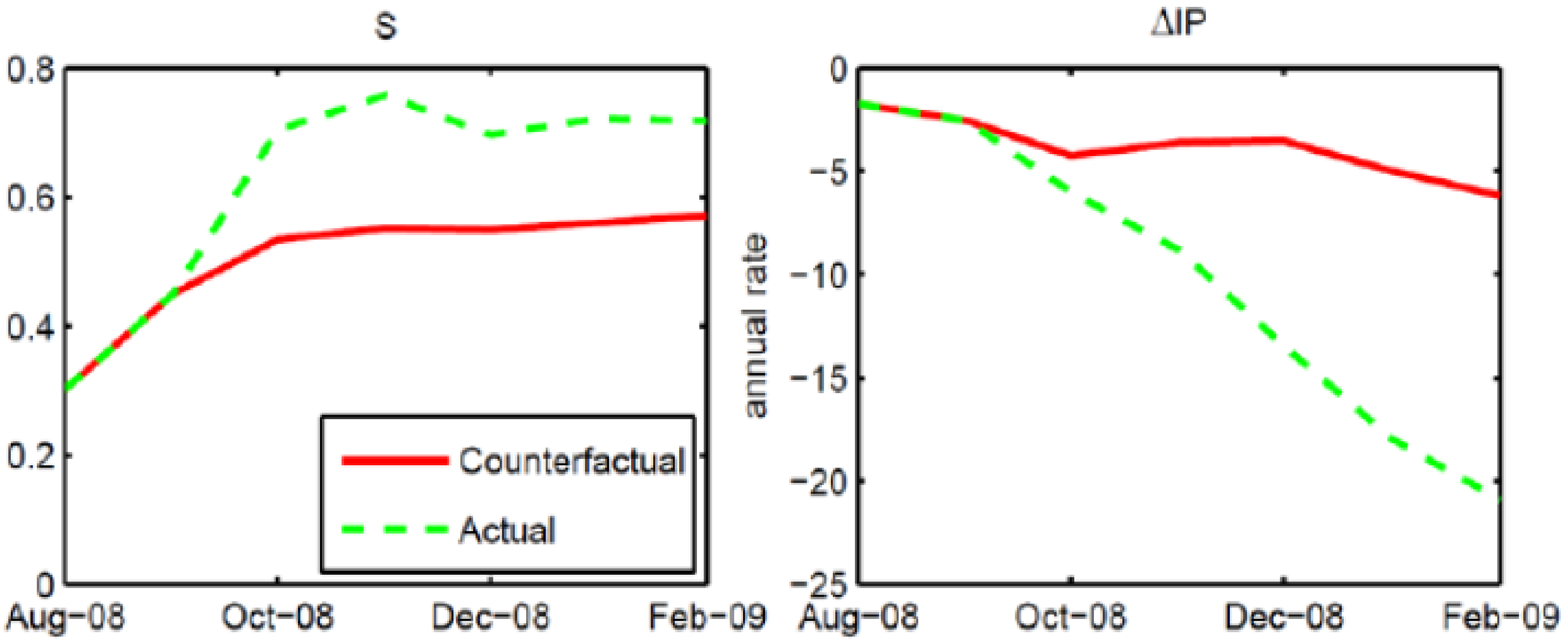
"systemic crisis" regime 6 (red line)
"tranquil times" regime 1 (blue dashed line)
linear VAR (black dotted line)





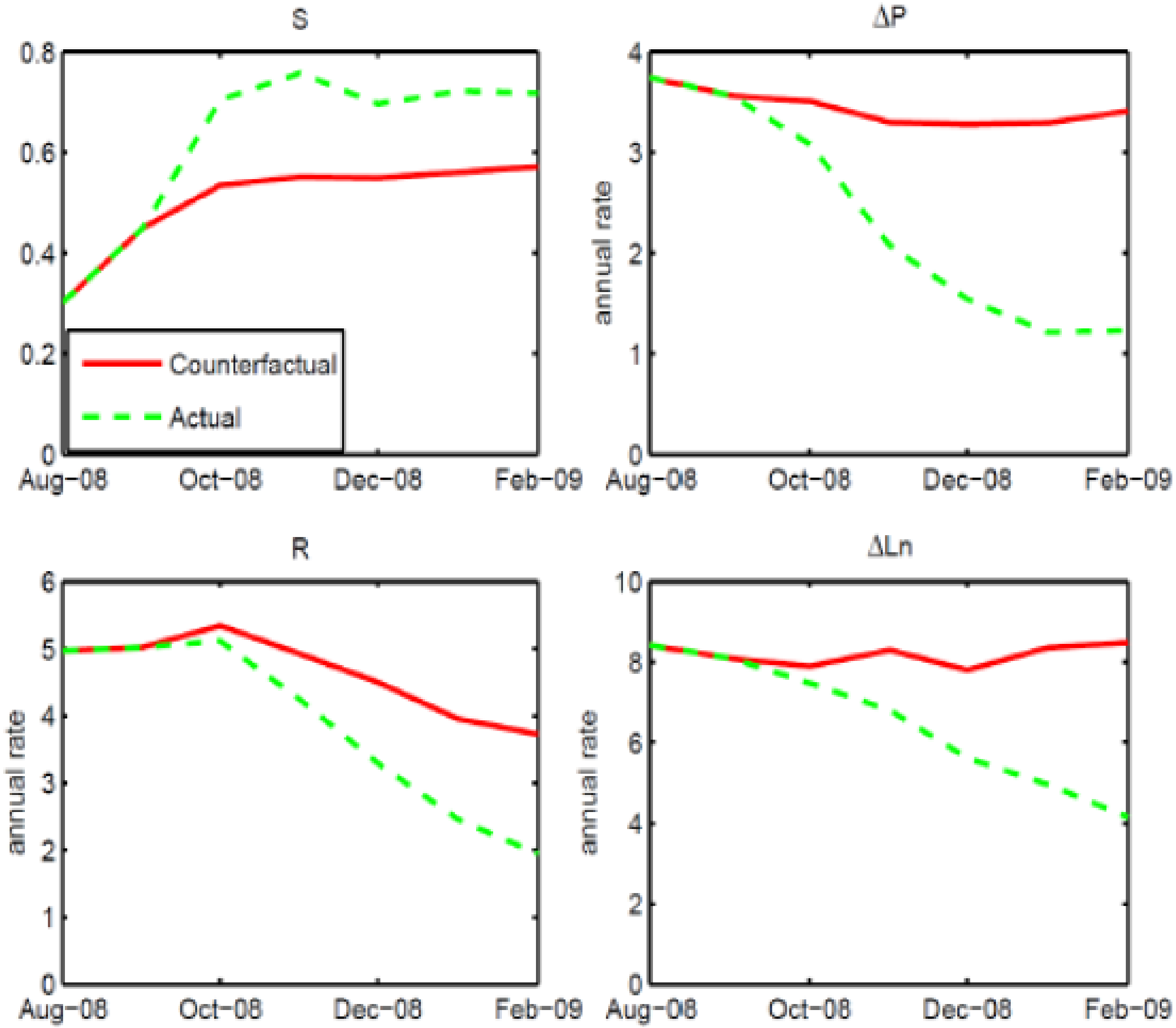
- **Protracted decline in loans**
- **Despite strong reaction of standard monetary policy**

3. Counterfactual analysis I



- **Counterfactual:** *Oct 2008 to Feb 2009, tranquil times (regime 1) instead of systemic crisis (regime 6)*
  - Financial stress (S) at considerably lower levels
  - Decline in industrial production growth (ΔIP) much more muted

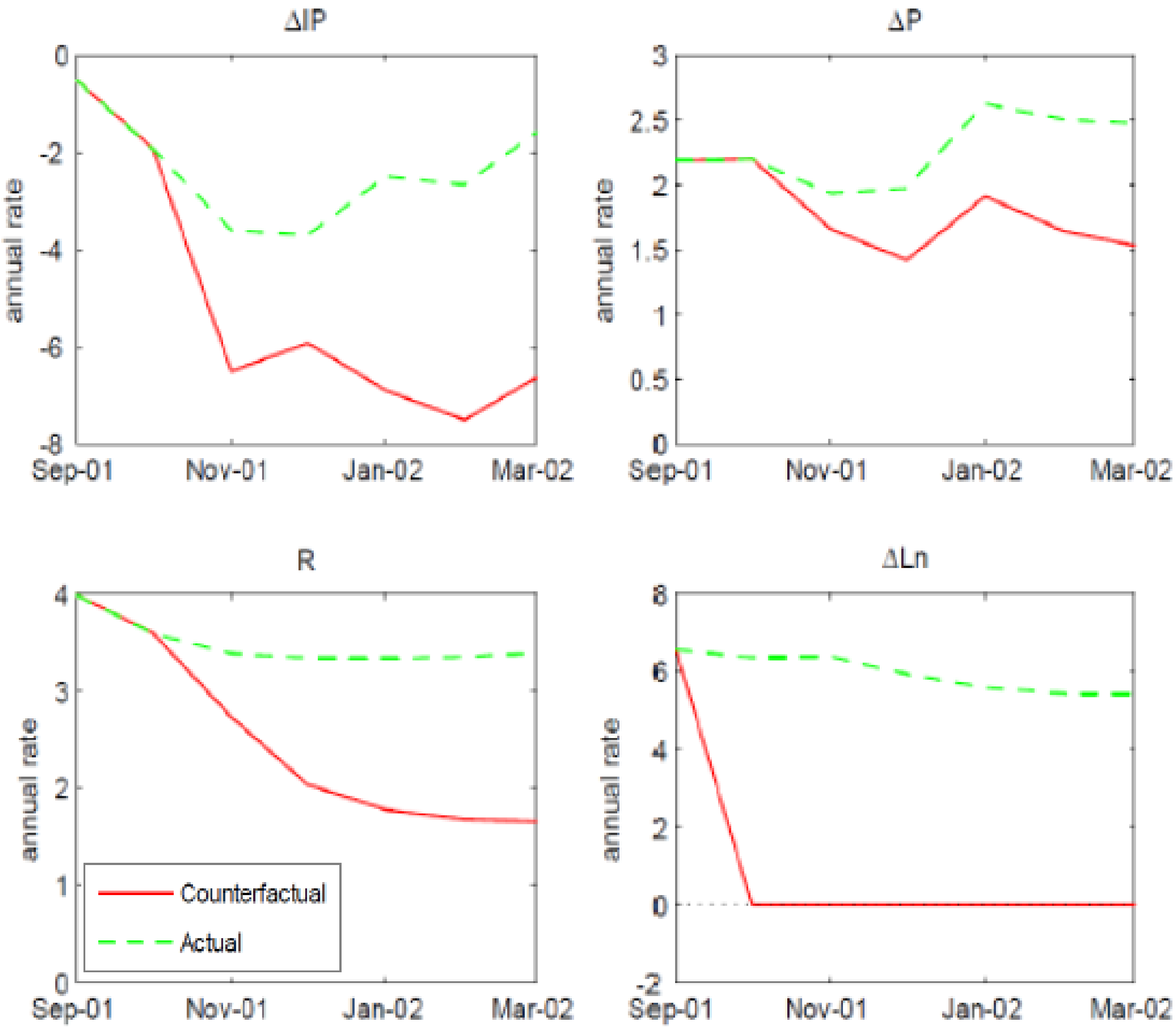
3. Counterfactual analysis I (cont'd)



Counterfactual: *Oct 2008 to Feb 2009, tranquil times (regime 1) instead of systemic crisis (regime 6)*

– Also inflation (ΔP), monetary policy interest rate (R) and loan growth (ΔLn) much lower

3. Counterfactual analysis II



Counterfactual: *Oct 2001 to Mar 2002 ("dot-com bust"), stable path of CISS at average level in that period, path in loan growth to 0% as in crisis*

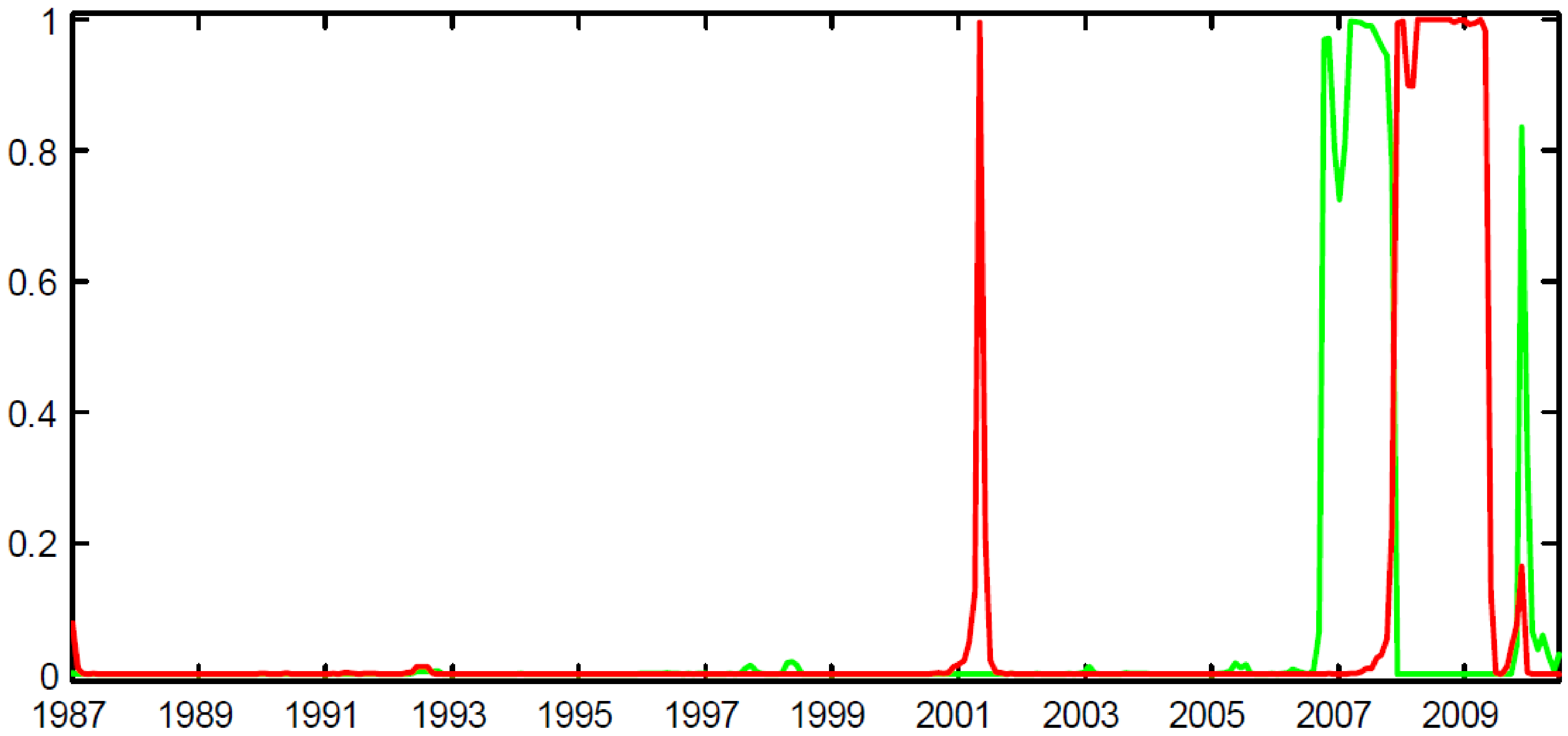
– Output growth (ΔIP), inflation (ΔP) and short-term interest rate (R) much lower

4. From subprime turmoil to systemic meltdown: A model tale

Smoothed regime probabilities

"systemic crisis" regime: high-stress variance + strong financial-real linkages

"systemic fragility" regime: high-stress variance + weak financial-real linkages



5. Concluding remarks

- During systemic crisis the macroeconomic dynamics change fundamentally (evidence of non-linearities)
  - Both the parameters characterising the structure of the economy and the sizes of shocks switch regime;
  - Hence, the severe output losses typically caused by systemic crises may not only result from large shocks but also from the amplified transmission of shocks to the real economy.

- Policy relevance
  - Model may help explain large macroeconomic forecast errors during the recent crisis;
  - Such MS-VAR models may improve macroeconomic now-casting or even forecasting during episodes of severe systemic stress and may therefore represent a useful addition to the analytical toolkit of monetary and macro-prudential policy makers.

Annex

Markov-Switching Vector Autoregression model

$$y'_t A_0(s_t^c) = \sum_{l=1}^{p} y'_{t-l} A_l(s_t^c) + z'_t C(s_t^c) + \varepsilon'_t\, \Xi^{-1}(s_t^v) \qquad \textbf{(1)}$$

y_t: vector of endogenous variables [nx1] ;

z_t: vector of exogenous variables and intercept terms; later assumed to be only intercepts [nx1];

ε_t: error terms, vector of random shocks [nx1];

Ξ: diagonal matrix containing the standard deviations of the shocks [nxn];

A_0 [nxn], A_l [nxn], C[1xn]: coefficient matrices;

s_t^c, s_t^v: unobserved state variables evolve according to two independent first-order Markov processes:

$$\Pr(s_t^m = i | s_{t-1}^m = k) = p_{ik}^m, \quad i,k = 1,2,..h^m \text{ , m=c,v} \qquad \textbf{(2)}$$

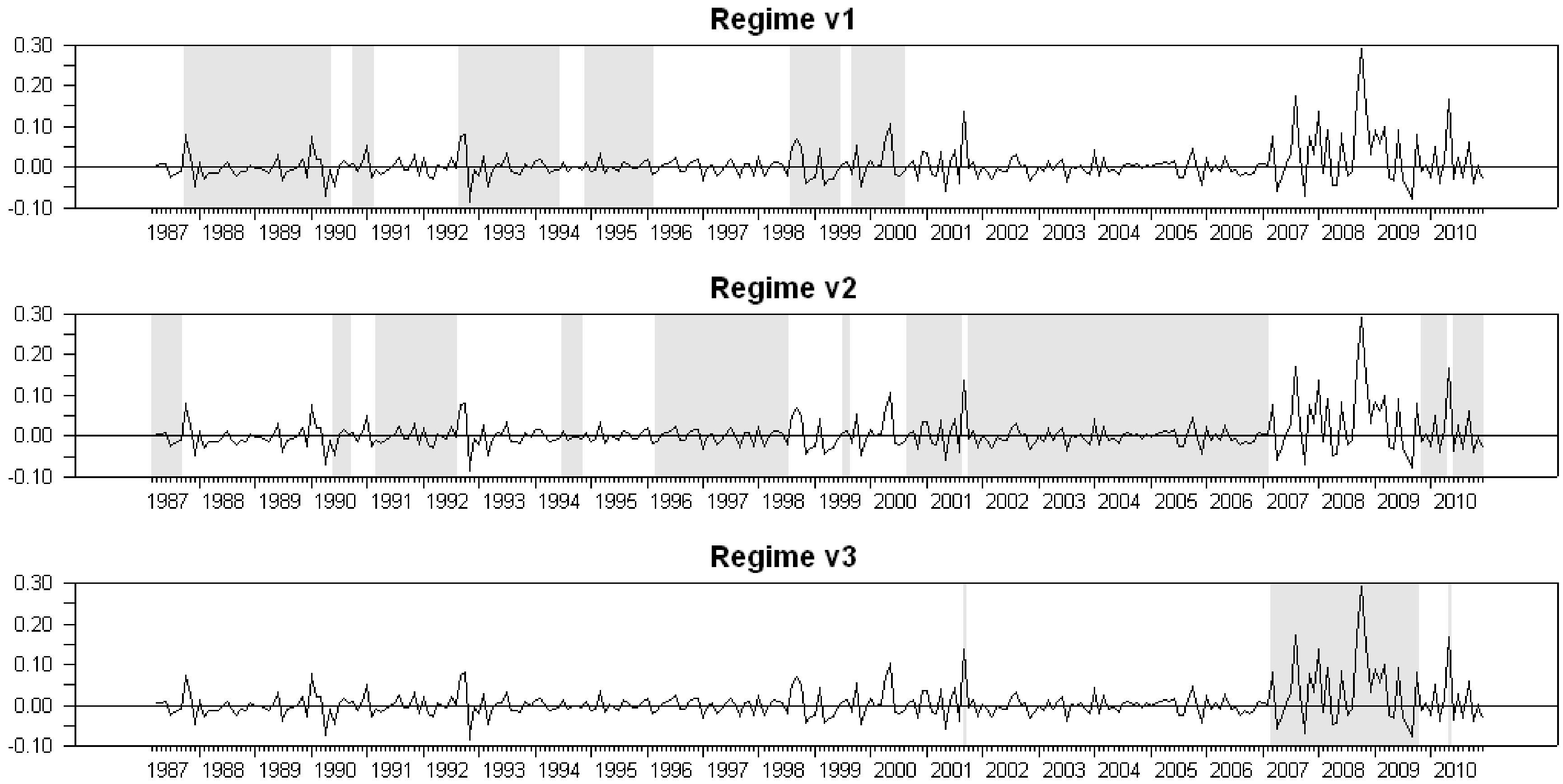
Let $Y^t = \{y_0, y_1, \ldots y_t\}$ as the vector y stacked in the time dimension, then the structural disturbances are conditionally normal:

$$\varepsilon'_t(s_t^v)|Y^{t-1} \sim N(0_{n\,x1}, I_n) \qquad \textbf{(3)}$$

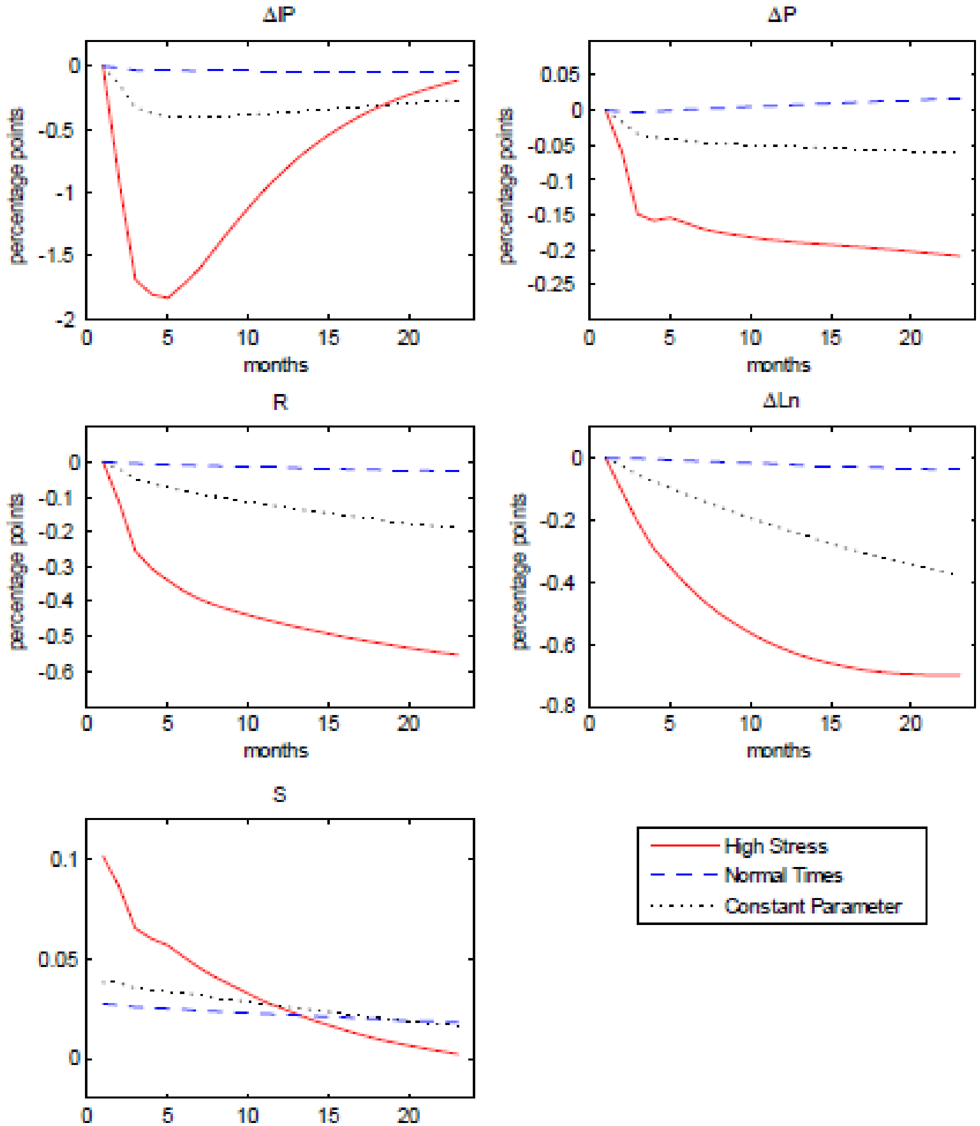
Model estimation and evaluation

- Bayesian methods generally following Sims, Waggoner and Zha (2008)
- Estimation of posterior mode ("most likely" estimate)
  - Blockwise optimisation algorithm
  - Parameters divided into blocks and initial guesses for the parameters used in a hill-climbing quasi-Newton optimisation procedure
  - Two sets of priors:
    - VAR coefficients: standard Minnesota priors
    - Transition matrix: Dirichlet prior
- Model evaluation: Marginal Data Densities (MDDs)
  - MDDs or posterior model probs are a measure of model fit (the higher, the better)
  - Computation according to Sims, Waggoner and Zha (2008)

CISS residuals and variance regimes
(regimes shaded)

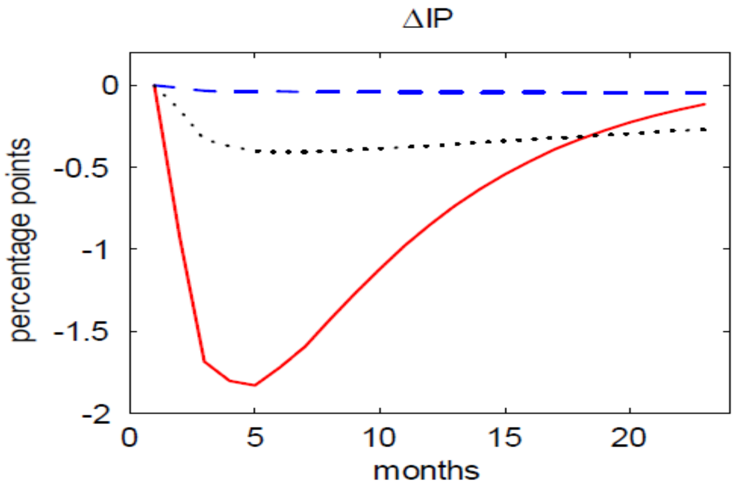


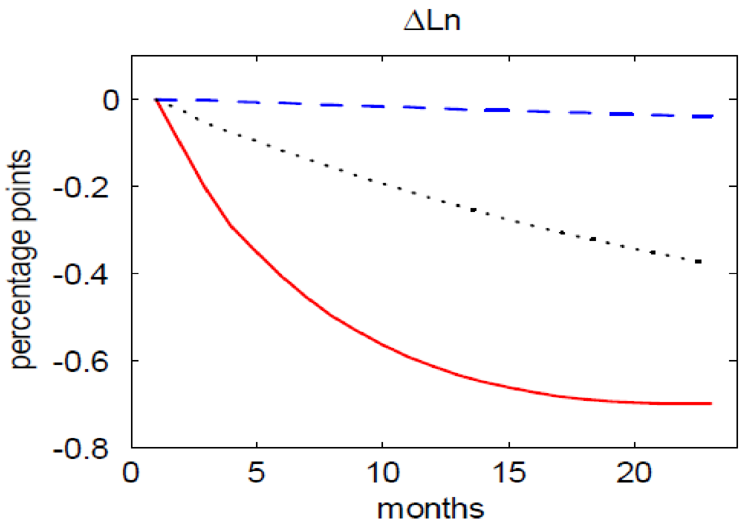
Full set of impulse response functions to CISS shocks



Alternative measures of financial stress: realised stock market volatility

1) IRFs with CISS





2) IRFs with stock market vola.